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PERFORMANCE EVALUATION OF CONTROL ALGORITHMS IMPLEMENTED ON A REMOTELY CONTROLLED ACTIVE NOISE CONTROL LABORATORY

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The remotely controlled laboratory setup for Active Noise Control (ANC) developed by Blekinge Institute of Technology, Sweden provides an efficient learning platform for the students to implement and learn ANC algorithms with real world physical system, hardware and signals. The initial laboratory prototype based on a Digital Signal Processor (DSP) TMS320C6713 from Texas Instruments (TI) was successfully tested with Filtered-x Least Mean Square (F-XLMS) algorithm applied to control noise in a ventilation duct. The resources of the DSP platform used in the remote laboratory setup enable testing and investigating substantially more challenging and computationally demanding algorithms. In this paper, we expand the horizon of the laboratory setup by testing more advanced and complicated single channel feed forward ANC algorithms. Filtered-x versions of algorithms such as the normalized least mean square (N-LMS), leaky least mean square (L-LMS), Filtered-U recursive least mean square (FURLMS) and recursive least square (RLS) algorithm etc. have been implemented utilizing the remote web based client provided in the remote laboratory. A comprehensive performance comparison of the aforementioned algorithms for the remote laboratory setup is presented to demonstrate the viability of the remote laboratory.

1. Introduction

There is a general consensus among educationalists concerning the importance of Educational Laboratory experiments in Engineering Education. Laboratory Experiments are a vital part of modern engineering curricula and are necessary for an adequate understanding of real world applications of the theoretical knowledge gained in the class room. To ensure high quality of laboratory education, certain guidelines or objectives are devised by accreditation boards such as, the Board for Engineering and Technology (ABET) USA, for laboratory education. The main aim of these guidelines is that students should acquire hands-on experience by working on physical systems and real instruments to be an effective engineer[1].

In laboratory experiments, students are exposed to operation and handling of real measurement equipment and real systems, on which they are supposed to carry out experiments. One frequent purpose is to compare the behaviour of the real systems with the behaviour suggested by their corresponding mathematical models. The limitations of the models and the measurement technology may be studied here. Laboratory experiments help students to develop experimental and analysis skills, creativity, team work, learning from failure, communication skills and train them for their professional careers.

1.1 Remotely controlled Laboratories: Benefits and development

Like other modes of education, laboratory experiments have also evolved thorough major development stages and had adopted the latest developments in technology extremely. With the rapid technology development in the industry, the demand for skilled engineers increases and thus hands-on experience based laboratory education. Pure simulation based experiments are beneficial for modelling and analysis but fail to deliver the benefits which hands-on experience based experiments may provide. On the other hand, increased number of students, high cost of laboratory equipment and the prevailing economic regression has unfortunately converted hands-on laboratory experiments from necessity to a luxury. The Information Technology boom had paved way for a new form of laboratory experiments, other than traditional hands-on and simulation based laboratories, known as remotely controlled through the Internet or web based or remote laboratories. In remote laboratories, real equipment and physical systems are controlled and accessed through Internet. Although, the student do not have a direct physical interaction with the system and equipment, which is a well debated detractor for remote laboratories. However, additional features such as audio, video feed back and a more descriptive web interface may enhance the user interaction with the equipment[2].

The idea of remotely control had now been transformed into global cooperation and sharing of laboratory resources among universities and industries through Internet with convenient accessibility and reduced developmental, maintenance and supervision costs[3,4]. Numerous individual as well as collaborative efforts from several universities can be seen during the past two decades to develop and share such laboratories. Blekinge University of Technology (BTH), Sweden early realized the benefits of remote laboratories and developed and shared remote laboratories with partner institutions under the well known Virtual Instruments Systems Instrument in Reality (VISIR) project[5,6]. The recently developed remotely controlled laboratory concerns active noise control and acoustic experiments[7].

1.2 Significance of remote experiments in active noise control

The ANC is based on a broad spectrum of disciplines such as signal processing, statistics, acoustics, measurement techniques, DSP hardware and software etc. Many well developed and mature control algorithms exist. To provide students in an ANC course with a relevant knowledge base in ANC, well designed and comprehensive experiments are required to complement the theory presented in the class room. A typical ANC experiment comprises of an application or a test bed to which active control is applied along with suitable sensors and analysis equipment e.g accelerometers and signal analyzer. A suitable DSP platform is also needed to implement the active control algorithms usually written in C/C^{++} programming or Assembly language. All these are practical learning tools and demand extensive experimentation. The equipment involved in an active control laboratory are expensive and usually a single setup is available for experiments. To increase the capacity of the limited resources, remotely controlled laboratories for active control experiments prove to be a viable solution.

1.3 Motivation for the work

The viability of the remote laboratory prototype facility was demonstrated for the Filtered-x Least Mean Square (FXLMS) algorithm along with the important steps involved such as ANC feasibility and system identification in[7]. A noise attenuation of up to 26 dB at one of the duct's resonance frequency was demonstrated. However, the laboratory's advanced resources may easily handle more computationally demanding and complex algorithms. Therefore, it was decided to evaluate the laboratory for a number of relevant active control algorithms and document their performance along with any problems pertaining to the use of the remote environment. This was a future step for the development of the remote ANC laboratory and to actually implement the laboratory in regular research and learning activities.

2. The ANC remote laboratory at BTH

To facilitate students and researchers involved in ANC, a novel multi purpose remotely controlled laboratory has been developed recently at BTH[7]. The subsequent sections discuss briefly the main components of the laboratory, while a detailed description of the laboratory can be found in[7].

2.1 The test bed and analysis equipment

The application for ANC in the remotely controlled laboratory is basically the control of low frequency noise in a ventilation duct! It is a well known problem that e.g. ventilation and air conditioning (HVAC) ducts generate low frequency noise[8,9]. The equipment for this application include a 4 *m* long circular duct, two loud speakers one acting as a noise source, the other as a control source and five battery powered low cost microphones as transducers. For the analysis of the microphone signals a four channel dynamic signal analyzer from HP (HP36570A) is used. The same analyzer is also used as e.g. a low frequency noise generator.

2.2 DSP platform

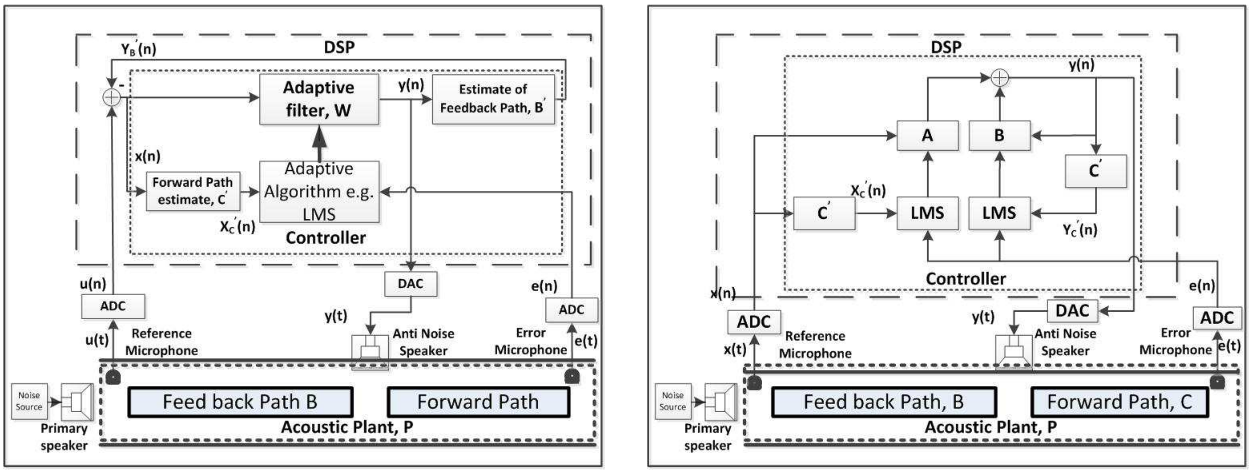
For the implementation of active control algorithms and signal processing algorithms for other tasks, a floating point DSP unit TMS320C6713 from Texas Instrument is used. The DSP card is equipped with a daughter card module (S. Module 16-100) from SEMATEC that supports four analog input and four synchronized analogue output channels. Both the analog-to-digital converters (ADC) and the digital-to-analog converters (DAC) have 16 bit resolution. The necessary signal conditioning for the input signals to the ADC and for the output signals from the DAC is carried out via software programmable filter/amplifier modules (USBPGF-S1/L) from Alligator Technologies.

2.3 Web interface and other equipment for remote control

Like a typical remotely controlled laboratory, students access the laboratory via a remote graphical user interface (GUI). The GUI is based on a client-server architecture consisting of two sub clients named as *Measurement and Configuration Client* and *Web-Based Development Environment*. The former is used to configure and control the speakers, microphones, filter modules and the signal analyzer. The later provides a basic Integrated Development Environment (IDE) for algorithm and signal processing tasks implementation similar to Code Composer Studio (CCS) for TI DSPs. The server facilities for equipment connection and web hosting are provided by Windows XP based HP Workstation. The laboratory equipment which require appropriate switching during ANC setup are connected to the server via a remote control switch or switching matrix, developed during the VISIR project. The switching matrix and the filter modules are connected to the server through Universal Serial Bus (USB) interface while the signal analyzer and DSP board are connected to the server by General Purpose Interface Bus (GPIB) and Joint Test Action Group (JTAG) interface respectively.

3. ANC for HVAC ducts

The ANC applied to the duct system of the remote laboratory is illustrated with the help of Fig. 1a. The controller W may be an adaptive finite impulse response (FIR) or infinite impulse response (IIR) filter, generates the output signal (control signal) $y(n)$ based on the signals $e(n)$ and $u(n)$ from error and reference microphones respectively. The practical complications introduced due to the acoustic paths and equipment present between the controller output $y(n)$ and error signal $e(n)$



(a) **(b)**

Figure 1. Block diagrams of ANC system for a ventilation duct. (a). A simplified single-channel feed forward ANC system for a ventilation duct. (b). Single-channel feed forward ANC system in context of the FURLMS algorithm implementation.

known as *forward path* and controller output $y(n)$ and reference signal $u(n)$, the *feed back path* are also shown. These paths also include the ADC, DAC, amplifier/filters, the control speaker and the relevant microphones. A suitable adaptive algorithm e.g. the filtered-x LMS, based on the least mean square (LMS) algorithm updates the coefficients $\mathbf{w}(n)$ of the adaptive FIR filter iteratively to minimize the noise at the error microphone location. The blocks C' and B' are FIR filter estimates of the *forward path* and *feed back path* respectively, needed for compensation of these paths. The estimation of these paths is discussed in section 4.1.

4. Active noise control: In perspective of the remote laboratory

To design and implement an ANC system, basically requires that a student have knowledge to: a). Determine the relevant dynamic properties of the system to be controlled, b). Determine the feasibility of ANC for the system, c). Understand and to implement suitable control algorithm on a DSP etc. The remote ANC laboratory enables for instance the students to perform all these important steps via the web based clients discussed in section 2.3. The following section describe briefly the implementation of these steps in the context of remote laboratory.

4.1 Implementation procedure and adopted methods

To ascertain the practicability of a single channel ANC for the duct system, its acoustic properties need a thorough investigation. The 315 mm diameter of the duct ensures a plane wave propagation below 630 *Hz* and hence a single channel controller i.e. one reference microphone, one error microphone and one ant-noise loudspeaker are likely to be sufficient for the ANC system [10]. The coherence function plot between error microphone and noise signal from the signal analyzer may provide information regarding the extent to which the error microphone signal can be linearly explained from the signal analyzer noise signal and may be utilized to estimate ANC performance prior to its implementation. The frequency response function (FRF) plot between the same signals revealed the eigen frequencies or frequencies where the energy of the noise is concentrated, for the duct system.

The forward and feed back paths were estimated using LMS algorithm, prior to ANC. For this purpose a band limited random noise generated by the signal analyzer was used as *identification signal*, connected to the anti noise speaker while the primary noise speaker was turned OFF. The necessary equipment configuration of the *Measurement and Configuration Client* for this purpose is shown in Fig. 2. To implement the LMS algorithm on the DSP board, the *Web-Based Development*

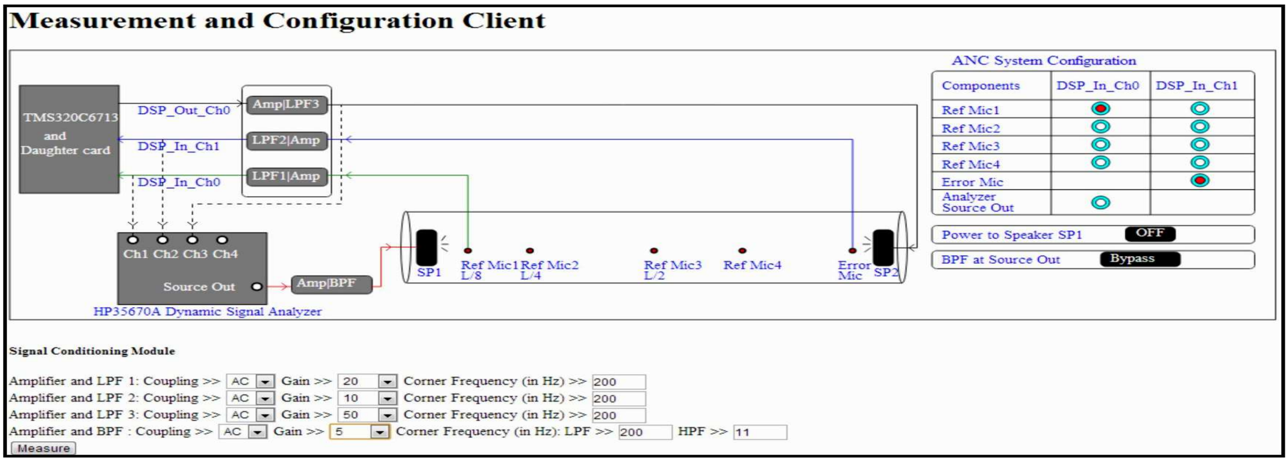


Figure 2. The Measurement and Configuration Client, for the configuration of equipment for a particular ANC application.

Environment client is instigated form the *Measurement and Configuration Client*. After convergence of the LMS, the estimates of the paths were saved for later use, to filter the signals as required by a particular ANC algorithm.

The implementation of ANC is similar to implementation of the *system identification* as described in the previous paragraph. The modifications required on the *Measurement and Configuration Client* are to turn ON the primary noise speaker, restore the role of the secondary speaker, connect the error microphone and select a proper reference microphone. A random primary noise in the range of 50-500 *Hz* was generated. The procedure was repeated for each algorithm and the noise attenuation was assessed by observing the power spectral density (PSD) of the error microphone with and without ANC at a narrow frequency range centred at 119 *Hz*, a duct eigen frequency. The PSDs of the error microphone before and during ANC are shown Fig. 3.

4.2 Normalized Least Mean Square (NLMS) algorithm

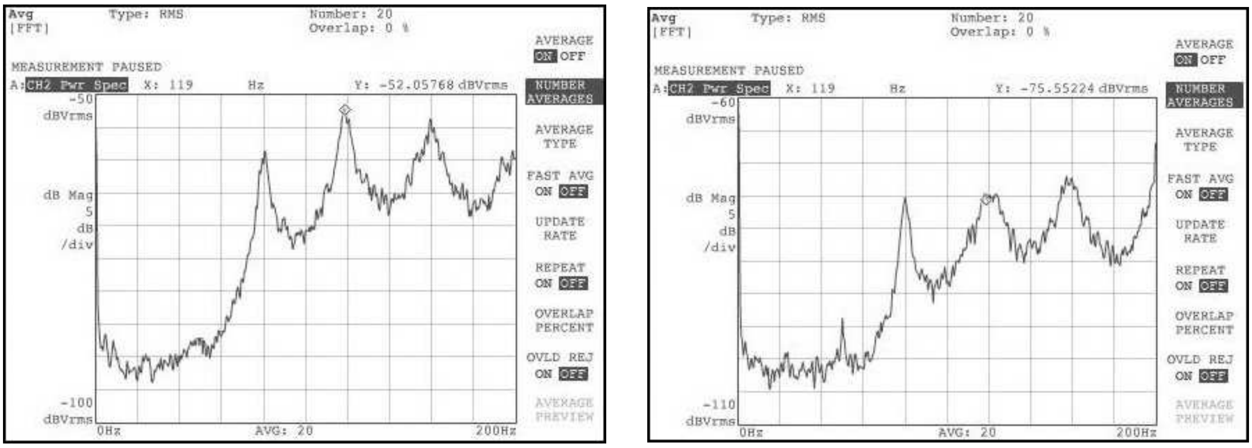
In the basic LMS or FXLMS algorithm, the value of μ determines the convergence speed of the adaptive filter and is sensitive to time variation in the power of the input or reference signal $x(n)$ [11]. This sensitivity to the input signal is neutralized by normalizing the step size μ with the energy (L_2-Norm) of the signal. The basic LMS algorithm vector update weight equation for $\mathbf{w}(n)$ can be modified as following

$$\mathbf{w}(n+1) = \mathbf{w}_n + \frac{\beta}{\epsilon + \parallel x(n) \parallel^2}\mathbf{x}(n)e(n) \tag{1}$$

Here, β is the new step size, $\parallel x(n) \parallel^2$ is the L_2 Norm of $x(n)$ and ϵ is a small positive real value which avoids division by zero in case $x(n)$ becomes zero. In order for the NLMS to converge in mean square sense, we should have $0 < \beta < 2$. The noise attenuation achieved using the NLMS is shown in Fig. 3. The attenuation is estimated from the PSD plots of the error microphone when ANC was off and ON at a particular frequency (119) *Hz* i.e. at the resonant frequency of the duct system used in the laboratory.

4.3 Leaky Least Mean Square (Leaky-LMS) algorithm

Some practical limitations of an ANC system may cause the LMS or FXLMS algorithm to suffer from stabilization problems such as insufficient spectral excitation and errors caused by overflow due to limited numerical precision in DSP. The insufficient excitation problem (zero eigenvalues in the input signal autocorrelation matrix) may result from placing a reference microphone at a pressure



(a) **(b)**

Figure 3. Noise attenuation attained when the NLMS algorithm was used. The noise attention can be seen at 119 *Hz* by comparing the PSD plots in (a) and (b). (a). PSD of the error microphone when ANC is OFF when ANC is OFF and (b). PSD of the error microphone when ANC is ON.

node and may cause un-damped modes in adaptive filter[11]. This problem may be avoided by adding a "leakage" factor ν to the coefficient update LMS algorithm.

$$\mathbf{w}(n+1) = \nu\mathbf{w}(n) + \mu\mathbf{x}(n)e(n) \tag{2}$$

The leakage factor ν is generally selected to have a value slightly less than 1 and has a restraining influence on the filter coefficients and avoids non-linear distortion in the secondary speaker by restraining its output at the cost of introducing a bias in the steady state solution[9,11].

4.4 Filtered-U Recursive Least Mean Square (FURLMS) algorithm

The acoustic *feed back path* B may also be modelled as part of the controller modelling the acoustic plant P shown in Fig. 1b. which introduces poles in the system transfer function and thus, can be modelled as an IIR filter[12]. The FURLMS algorithm by Feintuch is one of the several algorithms used for ANC using IIR filters[13]. The poles introduced by the acoustic feedback are eliminated by the poles of adaptive IIR filter[13]. The implementation of FURLMS in ANC system is shown in Fig. 3b. The convergence rate is slower as compared to adaptive FIR filters and its poles may introduce stability problems. Moreover, it might converge to local minimum and error signal is not guaranteed to be reduced at every iteration[11]. The output of the controller $y(n)$ for the FURLMS is given by

$$y(n) = \sum_{i=0}^{M-1} a_i x(n-i) + \sum_{j=1}^{L} b_j y(n-j) \tag{3}$$

Where a_i is the weight vector of the path A, b_i is the weight vector of the path B while M and L are their respective orders. The weight update equations for the FURLMS are given as[9,13]

$$a(n+1) = a(n) - \mu e(n) x'_C(n) \tag{4}$$

and

$$b(n+1) = b(n) - \mu e(n) y'_C(n-1) \tag{5}$$

Where $x'_C(n)$ and $y'_C(n)$ are filtered reference and controller output signal respectively, filtered by C', FIR filter estimate of the *forward path* C.

4.5 Recursive Least Square (RLS) algorithm

The RLS algorithm minimizes the energy of the instantaneous error signal (vector) $e(i)$ by optimizing the filter coefficients thorough least squares. In RLS algorithm, the filter coefficients need to be updated for every incoming data. Thus, there will be different filter coefficients even for the data having same statistical properties[11]. The RLS has a smaller steady state error and faster convergence but the computational complexity is higher as compared to the LMS[9]. The exponentially weighted RLS is implemented using the remote laboratory. The weight vector $\mathbf{w}(n)$ for the FIR implementation of the RLS including the effect of the secondary or forward path is given as

$$\mathbf{w}(n+1) = \mathbf{w}(n) + \mathbf{k}(n)e(n) \tag{6}$$

Where $k(n)$ is the gain factor and is equal to

$$\mathbf{k}(n) = \frac{\lambda^{-1}\mathbf{Q}(n-1)\mathbf{x}'_C(n)}{\mathbf{x}'^T_C(n)\lambda^{-1}\mathbf{Q}(n-1)\mathbf{x}'_C(n)) + 1} \tag{7}$$

$\mathbf{Q}(n)$ is the inverse of the input autocorrelation matrix evaluated recursively, $\mathbf{x}'_C(n)$ is the vector of the filtered input signal, filtered by C' and $\mathbf{x}'^T_C(n)$ is transpose of $\mathbf{x}'_C(n)$. Finally, the controller output $y(n)$ and the error signal $e(n)$ are given by

$$y(n) = \mathbf{w}^T(n)\mathbf{x}(n) \tag{8}$$

$$e(n) = d(n) - \mathbf{c}^T(n)\mathbf{y}(n) \tag{9}$$

Where $\mathbf{c}(n)$ is the impulse response vector of the *forward path* C.

5. Performance comparison

The attenuation results for all the algorithms implemented on the remote laboratory are presented in Table. 1. The order of the filter along with the number of operations i.e. multiplications, additions and memory usage required for the algorithms are also documented. The estimates of the filter order are represented by the same symbols as they were used in the algorithm. The order of the FIR filter estimates for the *forward path* C' used is equal to the order of FIR filter estimates for the *feed back path* B', so only C' is presented. These numbers shows that the DSP and hence the laboratory setup is capable of handling these computations.

Table 1. Performance comparison of the adaptive algorithms.

Algorithm	Noise Reduction (dB)	Computational Complexity			Filter order		
		Multiplication	Addition	Memory Usage	C'	B', A'	W
N-LMS	23.5	2N+4	2N+3	2N	128	–	256
L-LMS	24.5	3N+1	2N+2	2N	128	–	256
FURLMS	20.0	2N+3	2N+5	2N+M	128	128,128	128
RLS	27.7	$2N^2$+4N	1.5N^2+2.5N	N^2+2N	128	–	256

6. Conclusion and future work

The performance of the remote ANC laboratory prototype was evaluated by implementing gradient based and RLS based active control algorithms applied to low frequency noise in a ventilation duct. The achieved attenuation level for the algorithms used on the duct system is comparable. The GUI i.e. the *Measurement and Configuration Client* of the laboratory provides a simple but robust mechanism for the control of different transducers and speakers pertinent to the requirement of an

ANC algorithm. The processing power of the DSP and available daughter card module to incorporate more channels make the system suitable for more advanced and complex ANC systems and algorithms. Both researchers and students across the globe can access the laboratory via the Internet.

Being a prototype, the laboratory's performance is satisfactory. To increase the student's perception of being physically present and more involved, future work will focus on adding audio and video facilities along with a robotic system for moving the microphones. The *Measurement and Configuration Client* also requires changes to accommodate for multi channel ANC implementation. To give students more control of the DSP resources the *Web-Based development Environment* client of the laboratory will also be improved in near future.

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