#### Automatica 69 (2016) 1-11

Contents lists available at ScienceDirect

### Automatica

journal homepage: www.elsevier.com/locate/automatica

# Maximum likelihood least squares identification method for active noise control systems with autoregressive moving average noise\*

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#### ARTICLE INFO

Article history: Received 8 June 2014 Received in revised form 8 November 2015 Accepted 27 January 2016

Keywords: FxLMS Active noise control Least squares Online secondary path modeling Parameter estimation Maximum likelihood

#### 1. Introduction

Active noise control (ANC) has been receiving much attention for its ability to attenuate low frequency unwanted noise by generating an anti-noise which destructively interferences with primary noise in the desired zone (Kuo & Morgan, 1996; Lueg, 1936). The first design of ANC system that utilized an electronically driven speaker and a microphone was patented by Lueg in 1936 (Lueg, 1936). Basic configuration of feed-forward ANC system is shown in Fig. 1. In a feed-forward system, reference signal x(n)is detected by a reference microphone before it passes through primary acoustic path. An error microphone is used to pick up the residual noise e(n) and an adaptive noise control filter is deployed to generate the canceling signal. A noise control filter is usually adapted by Filtered-x least mean square (FxLMS) algorithm. The effectiveness of FxLMS algorithm is established by its presence in several developments in ANC systems (Ahmed, Akhtar, & Zhang, 2013; Akhtar, Abe, & Kawamata, 2006, 2007; Aslam & Raja, 2015; Carini & Malatini, 2008; Davari & Hassanpour, 2009; Eriksson & Allie, 1989; Kuo & Vijayan, 1997; Zhang, Lan, & Ser, 2001, 2003). In this algorithm, an estimate of secondary path (which includes digital-to-analog converter, reconstruction filter, power amplifier,

 $\stackrel{\,\,{}_{\infty}}{}$  The material in this paper was not presented at any conference. This paper was recommended for publication in revised form by Associate Editor Antonio Vicino under the direction of Editor Torsten Söderström.

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http://dx.doi.org/10.1016/j.automatica.2016.02.011 0005-1098/© 2016 Elsevier Ltd. All rights reserved.

#### ABSTRACT

Maximum likelihood methods are significant for parameter estimation and system modeling. This paper derives a maximum likelihood principle based least squares identification algorithm for online secondary path modeling in feed-forward active noise control systems with autoregressive moving average noise. This derivation proves that minimizing the cost function of least squares is equivalent to the maximum of likelihood function. Proposed method requires tuning of only one parameter in comparison with other recognized methods. Simulation tests show that proposed algorithm has better estimation accuracy and noise reduction capability than the current state-of-the-art methods in the presence and absence of disturbance at the error microphone.

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loud speaker, acoustic path from loud speaker to error microphone, error microphone, pre-amplifier, anti-aliasing filter and analog-todigital converter) is required for updating the filter coefficients (Kuo & Morgan, 1996). The impact of secondary path estimation error in reducing the stability and noise reduction capability of ANC systems is studied in detail in Ardekani and Abdulla (2012), Sato and Sone (1996), Snyder and Hansen (1994) and Tobias, Bermudez, and Bershad (2000).

Secondary path modeling has been receiving a great deal of attention in parameter estimation and identification (Ahmed et al., 2013; Akhtar et al., 2006, 2007; Aslam & Raja, 2015; Carini & Malatini, 2008; Davari & Hassanpour, 2009; Eriksson & Allie, 1989; Gaiotto, 2013; Kuo & Vijayan, 1997; Tyagi, Katre, & George, 2014; Zhang et al., 2001, 2003). However, acoustic paths are timevarying in nature due to environmental modifications, thermal variations and component aging (Kuo & Morgan, 1996). One way to address this problem is to use methods which do not require secondary path estimation like the evolutionary computing algorithms (Chang & Chen, 2010; George & Panda, 2012; Rout, Das, & Panda, 2012). Another way to tackle this issue is the online estimation of secondary path parameters. Eriksson et al. proposed the on-line transducer modeling in an adaptive active attenuation system using random noise (Eriksson & Allie, 1989). The noise reduction performance of this ANC system is degraded by continuous injection of unit variance auxiliary noise for secondary path modeling. Kuo et al. addressed this issue by injecting a low power auxiliary noise for secondary path modeling (Kuo & Vijayan, 1997). In comparison with previous methods, Zhang





Automatica Abrat 11 the industry Product About Case et al. improved the convergence speed and estimation accuracy by developing a cross-updation scheme (Zhang et al., 2001) and Akhtar et al. achieved improved convergence speed by the use of a variable step size LMS algorithm (Akhtar et al., 2006). In these methods, continuous injection of fixed variance auxiliary noise improves the modeling accuracy but increases the noise level at error microphone. Zhang et al. handled this issue by presenting an auxiliary noise power scheduling strategy with norm constraint manipulation (Zhang et al., 2003). In this strategy, noise power is varied in accordance with the power of the reference signal and the convergence status of ANC system. Similarly, Akhtar et al. extended the work in Akhtar et al. (2006) by introducing a noise power scheduling technique which uses power ratio of the modeling error signal and residual error signal for varying the power of auxiliary noise (Akhtar et al., 2007). Carini et al. proposed optimal variable step-size normalized LMS algorithms and auxiliary noise power scheduling for online secondary path modeling in feed-forward ANC systems (Carini & Malatini, 2008). This estimation algorithm responds poorly to the perturbations in acoustic paths. Davari et al. designed a robust online modeling technique for ANC systems that completely stops injection of auxiliary noise after the convergence of secondary path modeling filter (Davari & Hassanpour, 2009). Shakeel et al. presented a two-stage gain schedule for auxiliary noise in Ahmed et al. (2013). Initially, gain is varied in relation with power of modeling error signal. After achieving sufficient level of modeling accuracy, gain is varied on the basis of the correlation estimate of two consecutive samples of modeling error signal. Along with the improvement in performance of the ANC system, increase in number of tunable parameters makes room for improvement in the methods of Ahmed et al. (2013) and Carini and Malatini (2008). Gaiotto presented a tuning-less approach in secondary path modeling in Gaiotto (2013) without improving the estimation accuracy. Tyagi et al. proposed online estimation of secondary path in active noise control systems using generalized Levinson Durbin algorithm (Tyagi et al., 2014). Saeed et al. presented a variable step-size based fractional least mean square algorithm to improve the online secondary path estimation in Aslam and Raja (2015). In this scheme, the step-size increases in relation with the power ratio of modeling error signal and residual error signal. After convergence of modeling filter, power of modeling error signal dictates the step-size. Also, an upper bound is used to define the maximum value of step-size. Except Gaiotto (2013) and Tyagi et al. (2014), all the above mentioned algorithms use variations of slope gradient (SG) algorithm for parameter estimation, which has slow convergence rate as it does not make sufficient use of available data by using only the current data at each iteration (Ding & Chen, 2007). Also, the presence of disturbance at the error microphone degrades the noise reduction performance of above-mentioned algorithms. This disturbance arises in many real world applications like the noises generated by passing-by automobiles act as disturbance for ANC systems in electronic mufflers for automobiles. In industrial installations, machinery close to the location of error microphone can cause disturbance for ANC systems. ANC headsets for voice communications in noisy environments is another important example. Active headsets improve the speech quality for voice communication by canceling the primary noise that penetrates the passive ear muffs. In this case, the voice (or music for audio headsets) becomes a disturbance to the ANC system (Ahmed et al., 2013; Kuo & Morgan, 1996; Latos & Paweczyk, 2010). In this paper, we discuss a maximum likelihood least squares (MLLS) method for ANC systems with autoregressive moving average (ARMA) noises at error microphone. The maximum likelihood estimation method makes use of the information in the available data for computations at each iteration rather than using current data only (including the data from current and previous iterations) and gives

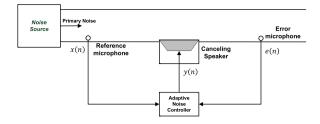


Fig. 1. Basic feedforward ANC system.

precise estimate of the distribution parameter estimates (Genschel & Meeker, 2010). Also, usage of MLLS algorithm for secondary path algorithm brings the advantage of zero tuning parameter as compared to above-mentioned algorithms.

Maximum likelihood estimation techniques are a class of important methods for dynamical system identification which have been discussed for a long time (Ljung, 1999) and have been applied to many areas such as spatial analysis (Kyung & Ghosh, 2010), image texture analysis (Lundahl, Ohley, Siffert, & Kay, 2007), asset pricing modeling in finance fields (Kayahan & Stengos, 2007) and speech recognition (Bahl, Jelinek, & Mercer, 2009). In recent years, numerous likelihood estimation methods are developed for different models. For example, Agüero et al. discussed the equivalence of time and frequency domain maximum likelihood estimation methods (Agüero, Yuz, Goodwin, & Delgado, 2010); Södersöm et al. performed an analysis on the accuracy of time domain maximum likelihood method and sample maximum likelihood method for output error identification and errors-in-variables (Södersöm, Hong, Schoukens, & Pintelon, 2010). Recently, Wang et al. derived the maximum likelihood method for the controlled autoregressive autoregressive systems (Wang, Li, & Ding, 2012) and controlled autoregressive autoregressive moving average systems (Wang, Ding, & Dai, 2012). This paper proposes a maximum likelihood least squares identification method for online secondary path modeling in the presence of ARMA disturbance at the error microphone, based on the maximum likelihood principle. In comparison with previous methods, the proposed method improves the estimation accuracy of secondary path modeling in the presence and absence of disturbance at error microphone. This improvement helps in enhancing the noise reduction capability of proposed ANC system.

The remainder of this paper is organized as follows: Section 2 establishes the signal flow in the proposed ANC structure. Section 2.1 derives the maximum likelihood objective function according to the maximum likelihood principle. Section 2.2 derives a maximum likelihood least squares algorithm for parameter identification. Section 2.3 presents the computational complexity analysis of the proposed ANC system. Simulation results are illustrated in Section 3 and concluding remarks are summarized in Section 4.

#### 2. Proposed methodology

The schematic of proposed methodology is shown in Fig. 2, where x(n) is the reference signal picked up by reference microphone, e(n) is the error signal detected by error microphone, P(z) represents the transfer function of primary path (transfer function from reference sensor to error signal), S(z) represents the transfer function of secondary path and W is the noise control filter of tap length L. The control-filter-output signal, y(n), can be computed as:

$$y(n) = \mathbf{w}^{T}(n)\mathbf{x}_{w}(n), \tag{1}$$

where  $\mathbf{w}(n)$  is the coefficient vector of noise control filter at time n and can be written as:

$$\mathbf{w}(n) = [w_0(n), w_1(n), \dots, w_{(L-1)}(n)]^I,$$
(2)

$$\mathbf{x}_{w}(n) = [x(n), x(n-1), \dots, x(n-(L-1))]^{T}.$$
(3)

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