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Robust Adaptive Inverse Control Based on Maximum Correntropy Criterion

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Abstract: Adaptive inverse control, proposed by Bernard Widrow, is mainly based on the well-known least mean square (LMS) algorithm. The LMS is a stochastic gradient algorithm under the minimum mean square error (MSE) criterion, which performs well for linear and Gaussian systems. However, its performance will become poor when signals are non-Gaussian, especially when systems are disturbed by impulsive noises. In this work, in order to improve the robustness of the adaptive inverse control against impulsive noises, we propose a new adaptive inverse control method, which is based on the recently developed maximum correntropy criterion (MCC) algorithm. The MCC algorithm aims at maximizing the correntropy between the model output and the desired response. Since correntropy is a nonlinear similarity measure that contains higher-order statistics of the signals and is insensitive to large outliers, the proposed method can achieve desirable performance in impulsive noise environments. Theoretical results on optimal solution and convergence are derived. Simulation results are also presented to demonstrate the superior performance of the new method.

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Keywords: Correntropy; adaptive inverse control; convergence analysis; robustness

1. INTRODUCTION

Adaptive filtering techniques are widely used in many different fields of signal processing, such as channel equalization, echo cancelation, system identification etc. In particular, adaptive filtering algorithms have been successfully applied in system control, and a novel control strategy called adaptive inverse control, was proposed by Bernard Widrow (Widrow and Stearns, 1985, Widrow and Walach, 2008). The basic idea of adaptive inverse control is to learn an inverse model as the controller to achieve adaptive control of unknown systems (or plants). The study on adaptive inverse control was initiated in the 1960s and at the first IFAC workshop a paper on adaptive inverse control including adaptive plant disturbance cancelling was presented by Widrow (Widrow and Walach, 1984). Later, several publications in neural network community focused on nonlinear adaptive inverse control (Psaltis et al., 1988, Hunt and Sbarbaro, 1991, Hunt et al., 1992). Recently, an adaptive inverse control of neural spatiotemporal spike patterns was also proposed by Lin Li (Li et al., 2013). Adaptive inverse control is easy to understand and use in practice for a person with some background knowledge about adaptive filtering. The least mean square (LMS), a well-known stochastic gradient algorithm under the minimum mean square error (MSE) criterion, is in general a basic adaptive filtering algorithm used in adaptive inverse control, due to its simplicity, efficiency, and strong tracking capability. The LMS performs well in most situations especially when the unknown system is linear and Gaussian. However, the performance (e.g. convergence speed, stability, steady-state misadjustment) of the LMS may degrade seriously when plants are disturbed by non-Gaussian noises, especially in the presence of impulsive noises with a heavy-tailed distribution (Parzen, 1962, Singh and Principe, 2012).

Recently, a novel similarity measure between two random variables, called correntropy, was proposed (Santamaría et al., 2006, Liu et al., 2007). The correntropy can be used as a cost function in robust regression or adaptive filtering, as it is a localized similarity measure, particularly with strong robustness against impulsive noises (or large outliers) (Liu et al., 2007, Chen and Principe, 2012). Under the maximum correntropy criterion (MCC), an adaptive filter can be updated such that the correntropy between the filter output and the desired response is maximized (Singh and Principe, 2009, Zhao et al., 2011). The steady-state convergence performance of adaptive filtering under MCC has been studied (Chen et al., 2014). In the present paper, we apply the correntropy to adaptive inverse control and propose the Filtered-X MCC algorithm. The new adaptive inverse control can achieve desirable performance in the presence of non-Gaussian impulsive noises. The convergence issues of the Filtered-X MCC algorithm have also been studied.

The rest of the paper is organized as follows. In section 2, we give a brief introduction about the MCC. In section 3 we develop the Filtered-X MCC algorithm and study its convergence problem. In section 4, we present simulation results to demonstrate the performance of the new algorithm. Finally, conclusion is given in section 5.

2. BRIEF REVIEW OF MCC

A generalized correlation function, called the correntropy, is defined as a localized similarity measure between two random variables X and Y (Santamaría et al., 2006, Liu et al., 2007):

$$V_\sigma(X,Y) = E[\kappa_\sigma(X-Y)] = \iint \kappa_\sigma(x-y) dF_{XY}(x,y) \quad (1)$$

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where E denotes the expectation operator, $F_{XY}(x,y)$ denotes the joint distribution function of X and Y, and $\kappa_\sigma(\cdot)$ is a translation-invariant Mercer kernel with bandwidth σ. In this paper, we adopt the following Gaussian kernel

$$\kappa_\sigma(x-y)=\frac{1}{\sqrt{2\pi}\sigma}\exp\left(-\frac{\|x-y\|^2}{2\sigma^2}\right) \tag{2}$$

Essentially, the correntropy represents a squared L_2 distance in kernel space, as one can derive

$$\|\varphi(x)-\varphi(y)\|_{\mathbb{F}}=\sqrt{\frac{1}{\sqrt{\pi/2}\sigma}-2\cdot\kappa_\sigma(x-y)} \tag{3}$$

where $\varphi(\cdot)$ denotes a nonlinear mapping induced by the kernel $\kappa_\sigma(\cdot)$, and $\mathbb{F}$ denotes the corresponding feature space (i.e. the reproducing kernel Hilbert space).

Fig.1 shows a typical scheme of adaptive filtering under MCC criterion, where the filter weights are updated such that the correntropy between the filter output y and the desired signal d is maximized. In most practical applications, the correntropy should be estimated from a finite number of samples. Thus, the cost function for adaptation is

$$\mathrm{J}_{\mathrm{MCC}}=E[\kappa_\sigma(d-y)]\approx\frac{1}{N}\sum_{i=1}^{N}\kappa_\sigma(d_i-y_i) \tag{4}$$

where $\{y_i\}_{i=1}^N$ and $\{d_i\}_{i=1}^N$ are, respectively, the filter outputs and desired signals with N samples (N is the sliding data length for online learning scenarios).

Assume that the weight vector of the adaptive filter is W_k at the k^{th} iteration. The MCC algorithm can be expressed as

$$W_{k+1}=W_k+\mu\nabla\mathrm{J}_{MCC} \tag{5}$$

where μ denotes the step size parameter, and $\nabla\mathrm{J}_{MCC}$ denotes the gradient of J_{MCC} with respect to W. To simplify the computation and improve the tracking capability, one can set $N=1$ and obtain the following stochastic gradient based MCC algorithm (assuming an FIR adaptive filter):

$$W_{k+1}=W_k+\frac{\mu}{\sqrt{2\pi}\sigma^3}\exp\left(\frac{-e_k^2}{2\sigma^2}\right)e_kX_k \tag{6}$$

where $e_k=d_k-W_k^{\mathrm{T}}X_k$ and X_k is a tapped input vector. The above algorithm can also be rewritten as

$$W_{k+1}=W_k+\mu_ke_kX_k \tag{7}$$

with $\mu_k=\frac{\mu}{\sqrt{2\pi}\sigma^3}\exp\left(\frac{-e_k^2}{2\sigma^2}\right)$. Thus the MCC algorithm (7) can be viewed as an LMS algorithm (Widrow and Stearns, 1985) with a variable step size μ_k. When a large error occurs (usually caused by an impulsive noise), the step size μ_k will approach zero (see Fig.2). This implies that the MCC algorithm has a strong outlier rejection capability. As $\sigma\to\infty$, the MCC algorithm reduces to the LMS.

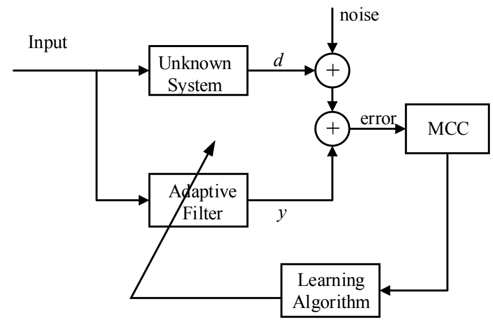

Fig. 1. Adaptive filtering under MCC criterion

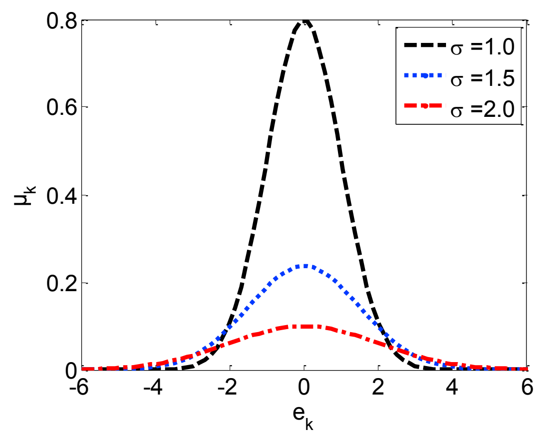

Fig. 2. μ_k as a function of e_k with different kernel widths

3. FILTERED-X MCC ALGORITHM

3.1 Filtered-X MCC

Adaptive inverse control is a relatively ingenious control method, which seeks an inverse model of the plant as its controller. With an adaptive filtering algorithm, an inverse model of the plant is learned and takes the series connection with the plant as a controller to control the dynamic response of the plant. The feedback in adaptive inverse control is some kind of local feedback, which is used to alter the model parameters to control primary loop's signal flow. So it is quite different from the conventional feedback control approach and belongs to open-loop control in some sense. A compromise generally exists between good dynamic response and good disturbance control in traditional feedback technology, but adaptive inverse control is a totally different one in that it separates the control process into two parts relatively independently: 1) the control of plant dynamic and 2) the control of plant disturbance. By this way the problem becomes simpler and easier to solve.

There exist some alternative configurations for adaptive inverse control realization and the Filtered-X MCC algorithm proposed in this work, inherits the fundamental structure from Filtered-X LMS algorithm, a very practical adaptive inverse control method (Widrow and Walach, 2008). Fig.3 depicts the configuration of the Filtered-X MCC algorithm. The upper part in Fig. 3 is to learn a model $\hat{\mathrm{P}}(z)$ of the

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