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[m1+;August 2, 2017;17:40]

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Journal of the Franklin Institute 000 (2017) 1-25

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# Sparse adaptive channel estimation based on mixed controlled $l_2$ and $l_p$ -norm error criterion

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Received 6 October 2016; received in revised form 22 April 2017; accepted 15 July 2017 Available online xxx

#### Abstract

In this paper, we propose sparse adaptive channel estimation algorithms based on a mixed controlled  $l_2$  and  $l_p$ -norm error criterion and zero attracting theory. In the proposed algorithms, a controlling parameter within the range of [0, 1] is adopted to control the mixture of the  $l_2$  and  $l_p$  norms which are exerted on the estimation error. The sparsity-aware characteristic is implemented by an  $l_1$ -norm penalty, a correntropy-induced metric penalty and a log-sum function constraint which are to exploit the in-nature sparseness of the channels. The proposed sparsity-aware algorithms give desired zero attractors in their iterations to speed up the convergence. The derivation of the proposed algorithms is presented in detail. We can find that the previously proposed sparsity-aware algorithms can be regarded as a special case of the proposed sparse adaptive algorithms. Also, the behaviors of the proposed algorithms are well verified over a multi-path wireless communication channel. As a result, our proposed algorithms are superior to the previously reported sparse mixed adaptive filters with respect to both the convergence and steady-state error for handling sparse signals.

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#### 1. Introduction

In recent years, there has been a surging interest in sparse signal processing for sparse channel estimation and sparse system identifications to improve the detection performance in classical signal averaging techniques [1–3]. Adaptive filters are regarded as useful method

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http://dx.doi.org/10.1016/j.jfranklin.2017.07.036

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Please cite this article as: Y. Wang et al., Sparse adaptive channel estimation based on mixed controlled  $l_2$  and  $l_p$ -norm error criterion, Journal of the Franklin Institute (2017), http://dx.doi.org/10.1016/j.jfranklin.2017.07.036

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[2,3] to detect time-varying potentials and to track the dynamic variations of a transmission signal [4,5], which learn the deterministic dominant signal and remove the noise signal. Also, adaptive filters can detect the shape variations in the ensemble and can give a good signal estimation. Thus, adaptive filtering technique has been widely used for channel estimation, echo cancelation and bioelectric signal processing. The least mean square (LMS) [6,7] is one of useful and extensively used adaptive filter algorithms due to its low complexity and easy implementation. Based on the classical LMS algorithm, several modified LMS or its variants [8–15] have been reported to improve its performance, such as signed LMS (SLMS) [10], normalized LMS (NLMS) [11,12] and variable step-size LMS algorithms [13,14]. However, these LMS algorithms are sensitive to the scaling of its input. Then, the least mean fourth (LMF) algorithm and its variants [16–18] have been presented based on the high-order moment (HOM) of the estimation error. Also, the mixture of the LMS and LMF algorithms [19–25] have been developed to overcome the drawbacks of the LMS algorithm, such as least mean square/fouth (LMS/F) [19] and least mean mixed norm (LMMN) [20,21,24,25] algorithms.

On the other hand, the LMS algorithm is regarded as optimum method when the noise statistics are Gaussian. If the noise is different from Gaussian, these HOM algorithms perform better than the LMS method such as LMF algorithm [16]. Also, a further improved algorithm is the mixture of both the LMS and LMF algorithms [19,26] in Gaussian environment. Additionally, these algorithms have been used for system identification in various environments. However, these mixed adaptive filtering algorithms are realized by using a fixed combination or a time-varying combination of the LMF and LMS algorithms, whose performance were controlled by introducing a mixture parameter. On the basis of these mixed-norm schemes [20–25] used in existing adaptive filtering algorithms, a modified method is given to overcome the disadvantages of the above existing mixed-norm adaptive filter algorithms, whose cost function is constructed based on the  $l_2$  and  $l_p$  norm criterions [27]. As a result, this modified algorithm can provide a better performance than the fixed mixture algorithms. However, the estimation performance of these adaptive filter algorithms may be degraded for sparse signal processing.

Recently, sparse adaptive filtering algorithms have been developed based on the zeroattracting (ZA) theory [8,14,17,18,20,26] and they are widely used for sparse channel estimation and echo cancelation. In [8,28], an  $l_1$ -norm constrained LMS algorithm and a reweighted ZA (RZA) LMS algorithm have been proposed and their estimation behaviors have been investigated over sparse systems. However, these sparse LMSs are still embarrassed in drawback of the traditional LMS algorithm that is sensitive to the scaling of the input signal. Similar to the development of the traditional adaptive filters [6,7,10,16,19], the ZA and RZA techniques have been expanded to the HOM algorithms, such least mean square/fourth (LMS/F) and LMMN algorithms [20-23,26,28]. The sparse mixed HOM algorithms are realized by combining the two-order, fourth-order error criterions and the  $l_1$ -norm penalty. Although these HOM algorithms with desired zero-attracting capability can improve the channel estimation performance, they introduce a tradeoff parameter to adjust the combination of the LMS and LMF schemes. In addition, the high-order error criterion in the sparse mixed HOM algorithms cannot be changed. Inspired by the above mentioned sparse adaptive filters, the zero-attracting techniques have been used for developing sparse affine projection (AP) algorithms [29,30], normalized LMS (NLMS) [31,32], set-membership NLMS (SM-NLMS) [33-35] and leaky LMS algorithms [36]. From the derivation and the performance investigation, we find that these algorithms have higher complexity than the ZA- and RZA LMS algorithms [8,28].

Please cite this article as: Y. Wang et al., Sparse adaptive channel estimation based on mixed controlled  $l_2$  and  $l_p$ -norm error criterion, Journal of the Franklin Institute (2017), http://dx.doi.org/10.1016/j.jfranklin.2017.07.036

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