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Zero-attracting variable-step-size least mean square algorithms for adaptive sparse channel estimation. (English) Zbl 1330.93248

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Summary: Recently, sparsity-aware least mean square (LMS) algorithms have been proposed to improve the performance of the standard LMS algorithm for various sparse signals, such as the well-known zero-attracting LMS (ZA-LMS) algorithm and its reweighted ZA-LMS (RZA-LMS) algorithm. To utilize the sparsity of the channels in wireless communication and one of the inherent advantages of the RZA-LMS algorithm, we propose an adaptive reweighted zero-attracting sigmoid functioned variable-step-size LMS (ARZA-SVSS-LMS) algorithm by the use of variable-step-size techniques and parameter adjustment method. As a result, the proposed ARZA-SVSS-LMS algorithm can achieve faster convergence speed and better steady-state performance, which are verified in a sparse channel and compared with those of other popular LMS algorithms. The simulation results show that the proposed ARZA-SVSS-LMS algorithm outperforms the standard LMS algorithm and the previously proposed sparsity-aware algorithms for dealing with sparse signals.

MSC:

93E24 Least squares and related methods for stochastic control systems
93C40 Adaptive control/observation systems
90B20 Traffic problems in operations research
93E10 Estimation and detection in stochastic control theory
93E03 Stochastic systems in control theory (general)

Keywords:

least mean square; sparse channel estimation; compressed sensing; zero-point attracting; l_1-penalized least Mean square; variable-step-size; adaptive filtering

Full Text: DOI

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