Improved Zero-Attracting LMS Algorithm for the Adaptive Identification of Sparse System

Ying Guo Haodong Wang Lily Li
Shenyang University of Technology

1 Introduction

The traditional LMS algorithm does not consider the characteristics of the system itself, and many systems such as underwater communication and TV transmission often show a kind of sparsity.

As the basis of this kind of algorithm, uses the L1 norm of the weight coefficient as the penalty term, and proposes ZA-LMS (Zero-Attracting LMS) algorithm. But ZA-LMS algorithm cannot distinguish between zero-valued weight coefficients and non-zero-valued weight coefficients, and imposes the same degree of zero-attraction on all coefficients.

At the same time, the fixed step size and regularization parameter make it difficult for the algorithm to achieve a good compromise between the convergence speed and the steady state error.

As mentioned above, we considering the aspects of the attraction operator, step size, and regularization parameter, an improved algorithm named VP-LZA-LMS (Variable Parameters and Logarithmic function based ZA-LMS) is proposed in this paper.

2 Methods

For enables the algorithm to exert different attractive force according to the value of the coefficient during updating.

- The logarithmic function is used to replace the original penalty term in ZA-LMS.

The variability of the step size and regularization parameter alleviates the contradiction between the convergence speed and the steady state error.

- Based on the minimized mean square deviation, the updated formulas are derived that can adjust the step size and regularization parameter in real time according to the error.

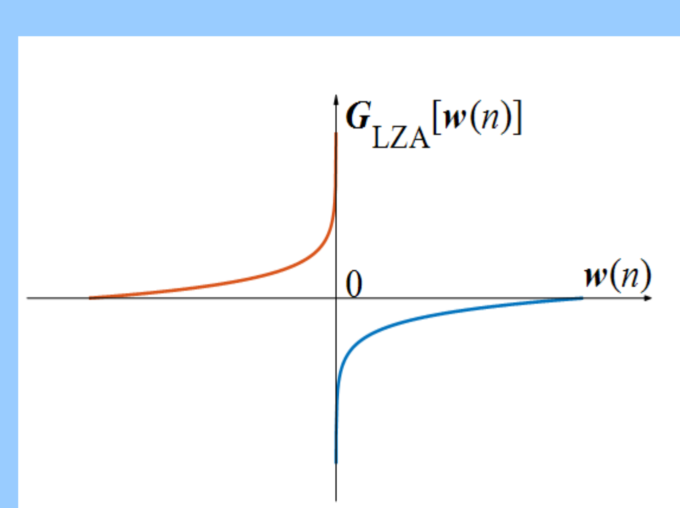

Fig.1 The new zero attractor

3 Results

Case1: Sparse System with Uncorrelated Input

In the first experiment, we considered an unknown system with SR=0.9177, which means the system is strongly sparse. The correlation coefficient $\alpha = 0$, so that the input signal was uncorrelated and Gaussian.

It is observed in Fig. 2 that the proposed algorithm significantly outperformed the other algorithms, by the reducing steady-state of NMSD.

Case 2:Sparse System with Correlated Input

In the second case, we used the same system as that of the first experiment except the correlation coefficient $\alpha = 0.5$, which means the input signal is not white.

As can be seen from Fig. 3, compared with Fig. 2, the performance of all algorithms is degraded when the input signal has a correlation. Compared with the other algorithms, the steady-state performance of the algorithm in this paper is better.

Case 3: Changed System with Correlated Input

In this case, we compared the tracking performance of the proposed algorithm with the other algorithms in three kinds of system.

The learning curves in Fig. 4 show that the proposed algorithm has more better track performance and lower steady-state error .

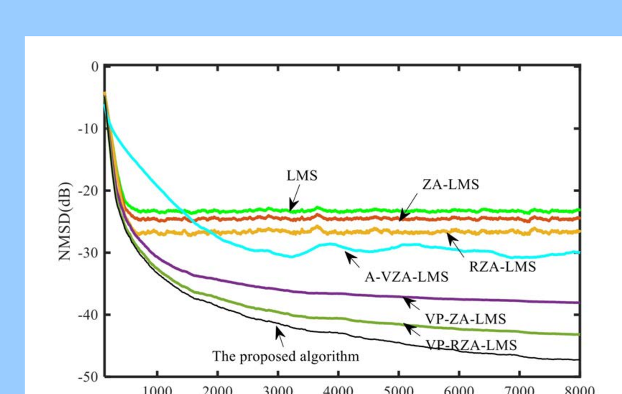

Fig.2 NMSD curve of the proposed algorithm and the others in the presence of strongly sparse systems driven by white Gaussian input signal.

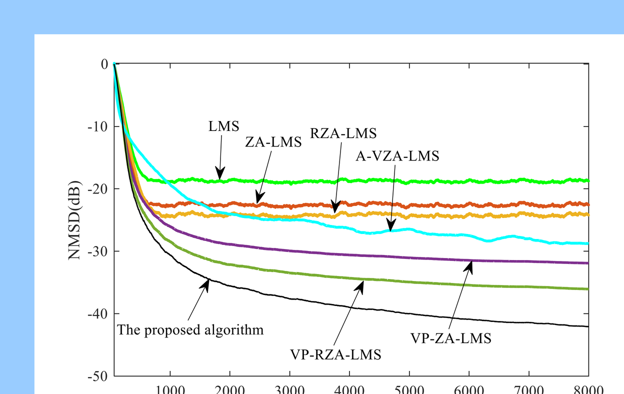

Fig.3 NMSD curve of the proposed algorithm and the others in the presence of strongly sparse systems driven by colored Gaussian input signal.

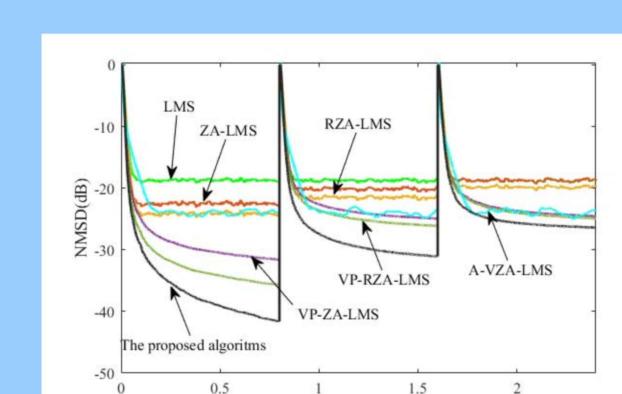

Fig.4 NMSD curve of the proposed algorithm and the others in the presence of time varying systems driven by colored Gaussian input signal.

4 Conclusion

In the proposed algorithm, the norm penalty term is modified in terms of the logarithmic function of the weight coefficients and the minimizing MSD is used to derive variable step size and variable regularization parameter.

The simulation results have revealed that the proposed algorithm can achieve better results when the input signal is correlated or uncorrelated. Compared with some existing algorithms, it has lower steady-state error and good tracking performance.

5 References

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