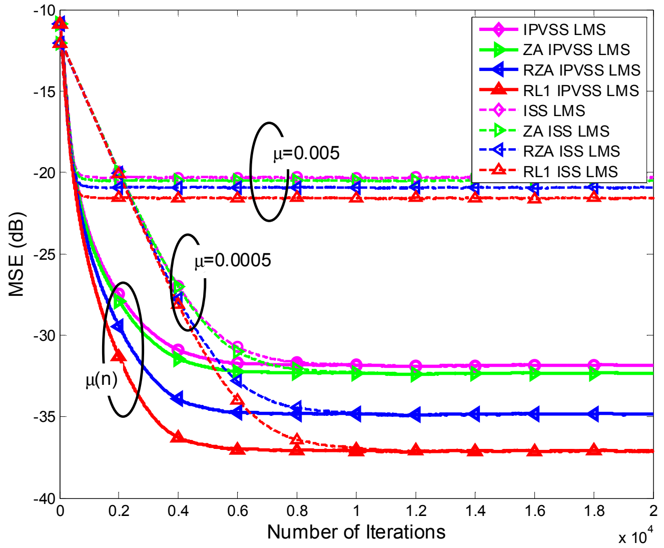

Fig. 3. MSE performance comparsion in the case of SNR=5dB and the channel sparsity *K*=8.

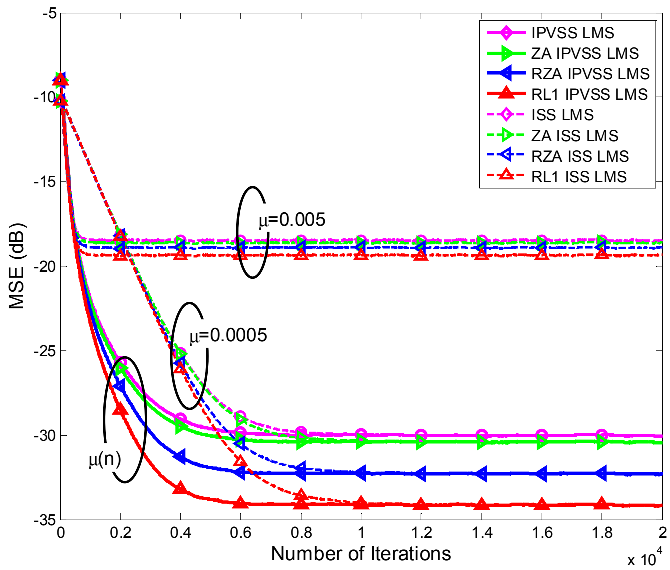

Fig. 4. MSE performance comparsion in the case of SNR=5dB and the channel sparsity *K*=12.

Let us take the Fig. 2 for example to illustrate the advantages of the proposed algorithms. In the case of 5dB, the number of non-zero coefficient is 4, they are compared with two groups of the performance curves of ISS-LMS for estimating sparse channel with different step- sizes (0.005 and 0.0005). In the first step, the proposed algorithms have a high speed convergence speed as same as ISS-LMS with step-size 0.005. When ISS-LMS with step-size 0.005 reach steady-state, the proposed algorithms continue to decline until $\mu(n) = 0.0005$. In the second step, the steady-state performance curves of the proposed algorithms are same as ISS-LMS with step-size 0.0005. While it is obviously find that the proposed algorithms have a faster convergence speed than ISS-LMS with step-size 0.0005. In other words, the proposed algorithms have the convergence speed of ISS-LMS with step-size 0.0005 both the estimation performance of ISS-LMS with step-size 0.005.

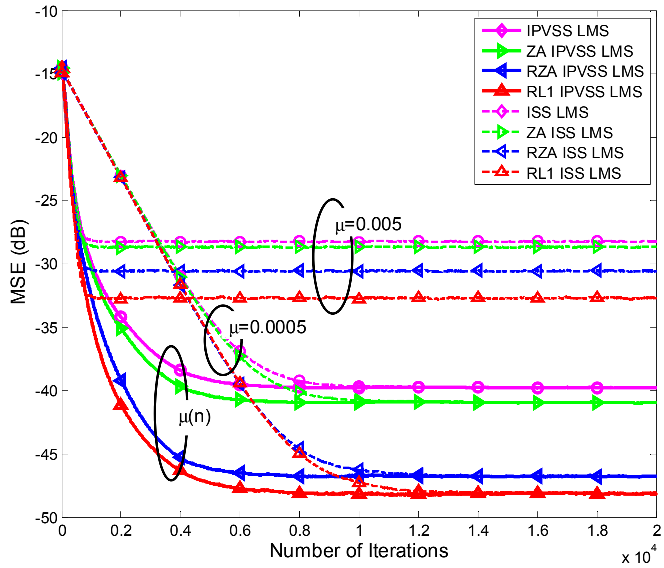

Fig. 5. MSE performance comparsion in the case of SNR=10dB and the channel sparsity K=4.

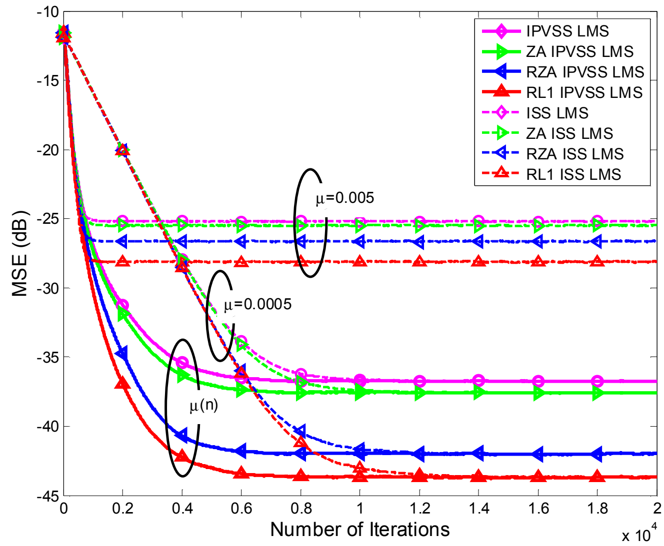

Fig. 6. MSE performance comparsion in the case of SNR=10dB and the channel sparsity *K*=8.

Fig. 8-10 demonstrate that the proposed channel estimation algorithms in the cased of 15dB, when different number of non-zero coefficient *K*. we can see that channel becomes smaller, namely the channel becomes sparser, the estimation performance of proposed algorithms can achieve better MSE performance than conventional sparse ISS-LMS algorithms with step-size 0.0005, while the convergence speed of the proposed IPVSS-LMS algorithms are faster than conventional sparse ISS-LMS algorithms. In Figs. 8-10, one can also find MSE performance of the proposed IPVSS-LMS algorithms are decided by the hard threshold φ, where smaller φ can bring better MSE performance but at the cost of convergence speed. Hence, selection of the threshold is also important technique to design the sparse IPVSS-LMS algorithms.

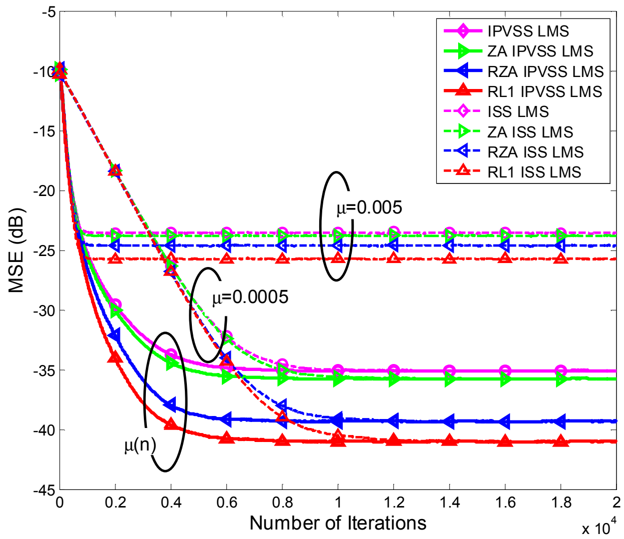

Fig. 7. MSE performance comparsion in the case of SNR=10dB and the channel sparsity K=12.

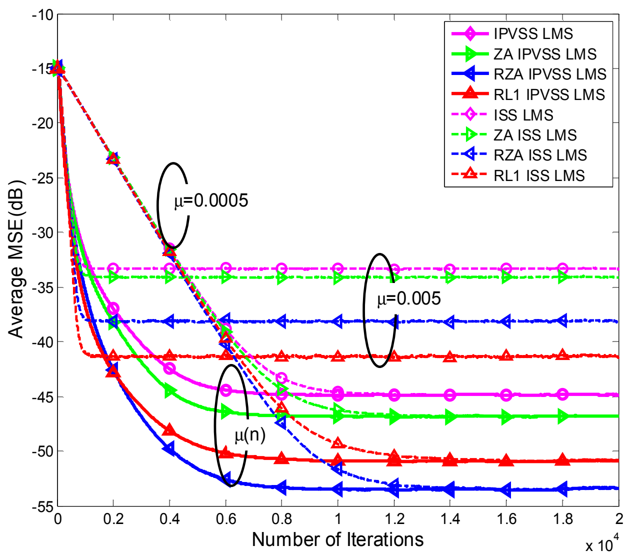

Fig. 8. MSE performance comparsion in the case of SNR=15dB and the channel sparsity K=4.

V. Conclusions

This paper has proposed three IPVSS-LMS algorithms to estimate sparse channels to accelerate the convergence speed. We first reviewed conventional sparse LMS algorithms, i.e., ZA-LMS, RZA-LMS and RL1-LMS and then presented the sparse IPVSS-LMS algorithms, i.e., ZA-IPVSS-LMS, RZA-IPVSS-LMS and RL1-IPVSS-LMS. The performance enhancement of the proposed channel estimation algorithms is achieved via designing VSS as well as exploiting channel sparsity. Compared to conventional sparse ISS-LMS algorithms, our proposed IPVSS-LMS algorithms can improve MSE performance while without scarifying convergence speed due to the fact that VSS is controlled only by iteration as well as threshold. Simulation results were provided to validate the proposed channel estimation algorithms.

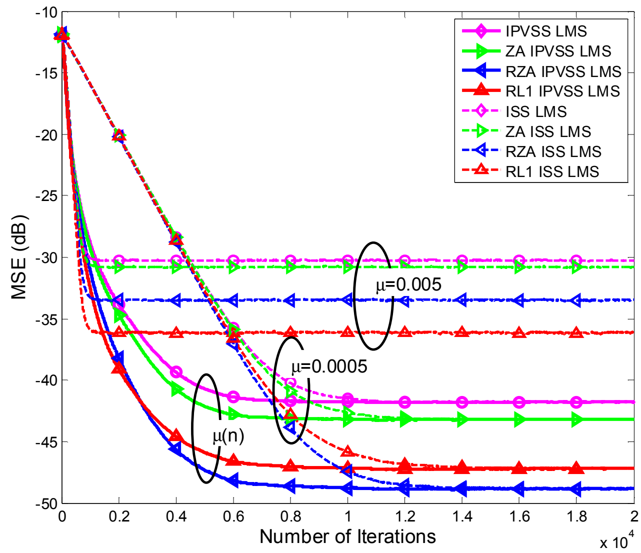

Fig. 9. MSE performance comparsions in the case of SNR=15dB and the channel sparsity K=8.

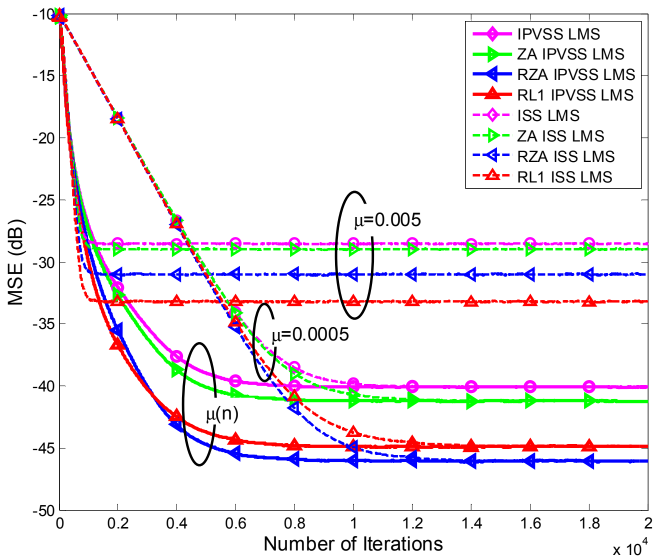

Fig. 10. MSE performance comparsions in the case of SNR=15dB and the channel sparsity K=12.

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