In Experiment 6, the basic \( \ell_p \)-RLS algorithm was compared with the stable sparse approximation using the \( \ell_q \) optimization (StSALq) algorithm [6]. The two algorithms were run using the settings of Experiments 1 and 2. The \( \ell_p \)-RLS algorithm was run many times with a different value of parameter \( \lambda \) in each time, and \( \lambda = 2 \times 10^{-3} \) was found to yield the best PoRIs. Similarly, for the StSALq algorithm, \( \mu = 4000 \) was found to yield the best PoRIs. Under these circumstances, the two algorithms were found to offer practically the same performance. The average CPU time obtained over 1000 runs is plotted versus the signal length, \( N \), in Fig. 6(b). As can be seen, the average CPU time required by the StSALq algorithm is one to two orders of magnitude larger than that of the basic \( \ell_p \)-RLS algorithm and is due to the fact that the former method requires the repeated use of matrix inversion as we stated in Section II-B.

In Experiment 7, the sensitivity of the SNR in the improved \( \ell_p \)-RLS algorithm to variations in the variance of the measurement noise was tested. The signal length, number of measurements, sparsity value, and variance were set to \( N = 512 \), \( M = 200 \), \( K = 90 \), and \( \sigma^2 = 10^{-3} \), respectively. The variance was then varied over the range \( 0.4 \times 10^{-3} \) to \( 1.5 \times 10^{-3} \), i.e., a total variation of \( \pm 150\% \). The average SNR is plotted versus the noise variance in Fig. 7. As can be seen, there is only a moderate variation in the SNR over this fairly large variation in the variance.

The proposed algorithms require the variance of the noise. State-of-the-art techniques for the estimation of the variance of the noise are available in the literature, for example, in [1], [2], and [3].

**REFERENCES**

