

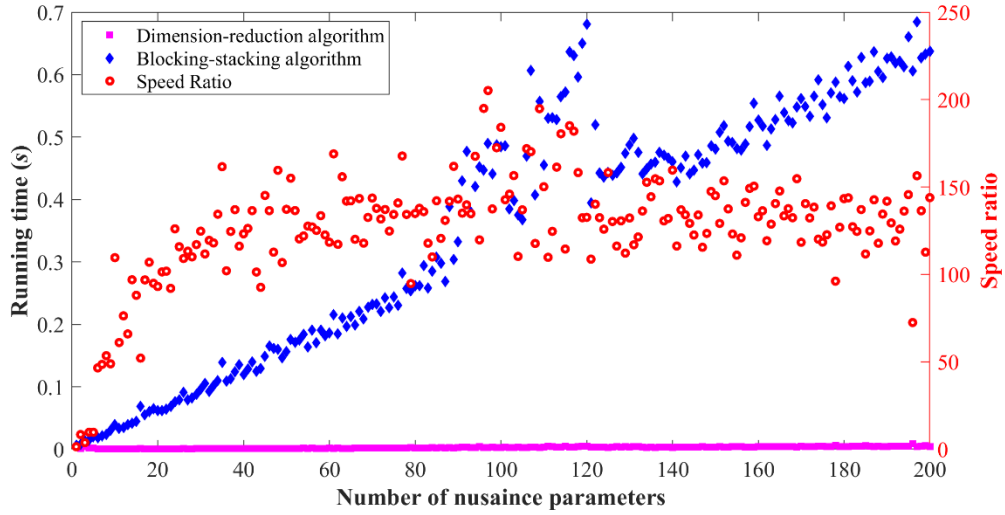
## 5.1 Experiential verifications

### 5.1 Dimension-reduction algorithm test

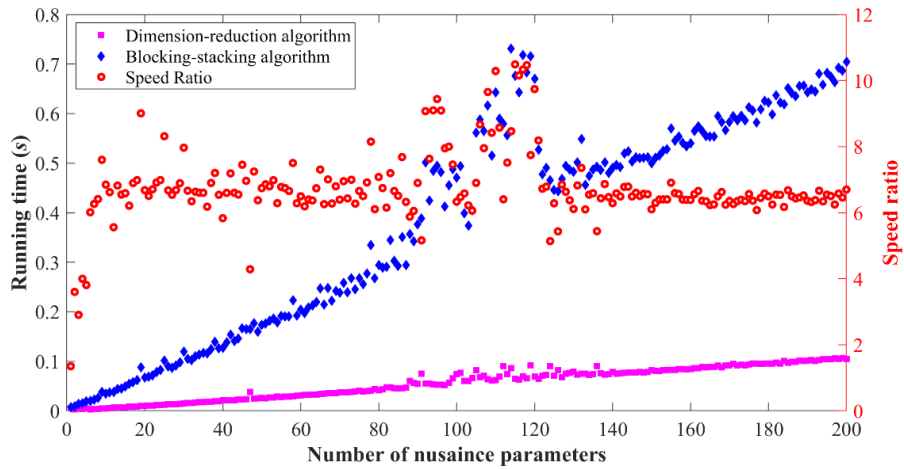
Coming back to the observation model (14), assume that the number of each set of observations  $L_j$  is  $n_j=1000$ , and the number  $q$  of nuisance parameters gradually increases from 1 to 200 to test the proposed algorithm performance. To illustrate the running speed of the algorithm, we define the index  $c=1/t$  where  $t$  is the running time of the algorithm to measure the speed, and then the speed ratio is defined as

$$k=c(\text{dimension-reduction algorithm})/c(\text{blocking-stacking algorithm})$$

is used to show the improvement of the proposed algorithm on the blocking-stacking algorithm.



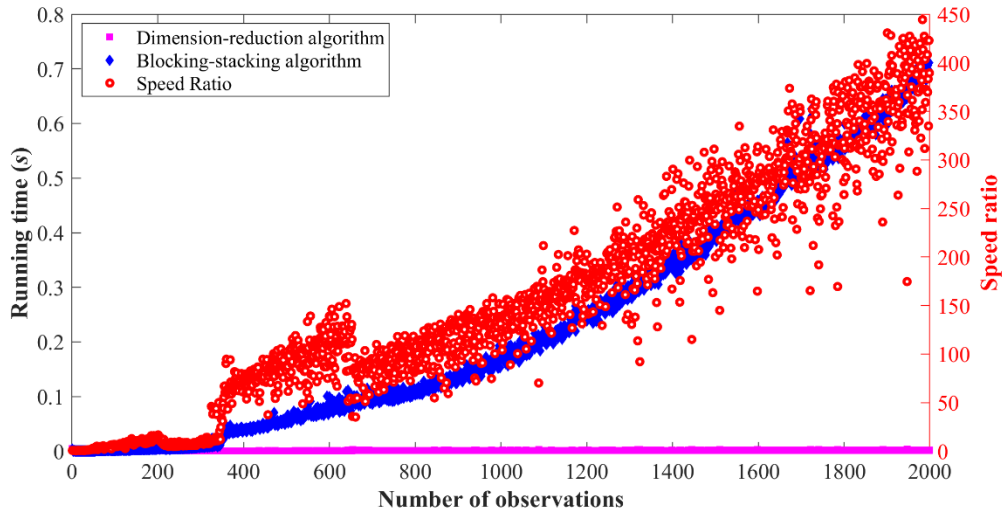
(a) equal-weight case



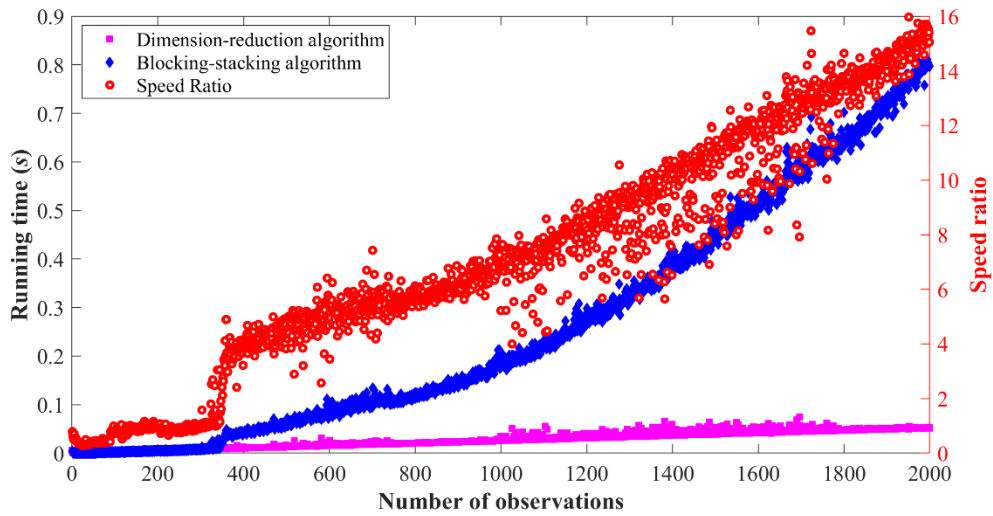
(b) unequal-weight case

Fig. 5 Running time increasing with nuisance parameters (fixed  $n_j=1000$ )

1 In the equal-weight case, Fig.5(a) shows that the running time of the blocking-  
2 stacking algorithm increases linearly with the number  $q$  of nuisance parameters, while  
3 that of the dimension-reduction algorithm increases very slowly and takes far less than  
4 0.1 second. The speed ratios show that the improvement of the proposed algorithm on  
5 the blocking-stacking algorithm is very effective, e.g., the former is more than 100  
6 times faster than the latter for the nuisances exceeding 30. In the unequal-weight case,  
7 as shown in Fig.5 (b), we can draw the same conclusion that the proposed algorithm is  
8 still more efficient and takes at most 0.1 seconds. Although the speed ratios become  
9 relatively smaller, it still increases linearly with the number of nuisance parameters, i.e.,  
10 the proposed dimension-reduction algorithm performance is still outstanding.



(a) equal-weight case



(b) unequal-weight case

**Fig. 6 Running time increasing with observations (fixed  $q=50$ )**

To test that the running time increases with the number of observations, we fix the dimension of the nuisance parameter,  $q=50$ , and then increase the number of each set of observations from 2 to 2000. As shown in Fig. 6, not only the dimension-reduction algorithm is still efficient, but also the running time of this algorithm is increased with the number of observations only linearly. This is a very good characteristic for the algorithm design to process a huge number of modern geodetic positioning observations.