One-Dimensional Prestack Seismic Inversion with Very Fast Simulated Annealing using Edge-Preserving-Smoothing Filter*

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Abstract

A hybrid technique based on very fast-simulated annealing (VFSA) to estimate the subsurface layer elastic parameters such as the P-wave velocity, the S-wave velocity and the bulk density is presented here. The technique introduces an edge-preserving-smoothing (EPS) filter to the VFSA algorithm in order to precondition the model space for blocky solutions. The algorithm leads to faster convergence and improved estimation compared to classical VFSA without the application of the EPS filters. Tests of the algorithm with different noise level and different random number generating seeds prove the stability and consistency of the algorithm.

Introduction

Estimations of the elastic parameters of the underlying earth layers are in the forefront of active research because of their importance in oil and gas exploration and reservoir characterization. Techniques involved in such estimations fall into two categories: linearized inversion (Smith and Gidlow, 1987) and stochastic inversion (Varela et al., 2006; Mallick, 1995). A new method based on hybrid stochastic optimization technique is proposed here. Very fast simulated annealing (VFSA), a variant of classical simulated annealing method, is used along with the edge preserving smoothing filters (AlBinHassan et al., 2006) to estimate the layer model parameters from an over-parameterized model space (Ma, 2001; Sen and Stoffa, 1991; Varela et al., 2006). The algorithm is tested on different noise levels to ascertain its stability. A comparison of the results indicates the effectiveness of the new algorithm as compared to VFSA optimization without application of the EPS filters. Further, the algorithm is tested with Monte-Carlo simulations for consistency.

Forward Model, Model Space and Edge-Preserving-Smoothing Filter

We used a forward model based on ray-tracing algorithm to generate predicted data at each VFSA iteration. The time-offset data are converted to the angle-domain by shooting rays from the source to receiver. The PP reflection coefficients are calculated from the Aki-Richards approximation of Zoeppritz equations. The angle-dependent reflection coefficients are further convolved with a known Ricker wavelet to generate synthetic data in the time-offset domain. We chose to use the ray-tracing method because it is computationally less expensive. However, performance of the algorithm should not be affected by replacing the current forward model with the reflectivity method.

We considered an over-parameterized model space consisting of the unknown model vectors, the P-wave velocity ($\boldsymbol{V_p}$), the S-wave velocity ($\boldsymbol{Vs}$) and the bulk density (ρ). The model space considered here comprised 30 layers (29 micro-layers over a half-space) of constant two-way travel time. The model space is bounded within ±15% of the respective true values. Following AlBinHassan et al. (2006), we designed an edge preserving smoothing filter. The EPS filter is obtained by considering several overlapping windows of pre-defined lengths. The middle value of the central window is replaced by the mean value corresponding to the window with least variability. The window with least variability is the one that has the least standard deviation. Such an array of windows is run over the entire model vector to obtain the EPS filtered output. Recently, Al-Dossary and Marfurt (2007) made a review of similar EPS filters. Figure 1 (a) and (b) demonstrate the effect of EPS filter on a model vector generated during a VFSA move. Degree of smoothness can be controlled by regulating the length of the filter and the number of times the filter is applied on the model vector.

Results and Analysis with and Without EPS Aided VFSA with Synthetic Data

The cost function is given by

$$J(m) = \left[\sum_{i=1}^{Noff} \sum_{j=1}^{Nt} \left| d(x_i, t_j)^{obs} - d(x_i, t_j)^{est} \right|^2 \right] \tag{1}$$

Where, J ($\boldsymbol{m}$) is the cost energy for model $\boldsymbol{m}$. Observed and estimated data for offset x_i and time sample t_j are given by $d\ (x_i, t_j)^{obs}$ and $d\ (x_i, t_j)^{est}$, respectively. A two-layer approach is followed to implement the EPS aided VFSA algorithm. In the first layer, VFSA algorithm works independent of the EPS filter. Accepted model is passed through the second layer and the cost function is evaluated with the EPS filtered output. The filtered model is accepted if there is lowering of the cost energy. The two-layer approach ensures that the optimization is performed without any bias towards any preferred blocky solution. Figure 2 (a) and (b) show the observed (SNR=20) and estimated synthetic data. Figure 3 (a), (b) and (c) show the estimated model parameters $\boldsymbol{V_p}$, $\boldsymbol{V_s}$ and ρ after 6000 evaluations of the cost function. Figure 4 (a) and (b) show the true and estimated data with SNR=10. Figure 5 (a), (b) and (c) show the estimated model parameters.

A comparison is made with the results obtained by using very fast simulated annealing without the application of the EPS filters. Figure 6 (a) and (b) show the true and estimated data. Figure 7 (a), (b) and (c) show the estimated model parameters obtained without the application of EPS filters. The shown results are obtained with 12000 evaluations of the cost function. The results show that improved model estimation and faster convergence could be achieved by applying the EPS filter in the global optimization scheme. The algorithm was further analyzed for uncertainty. One hundred Monte-Carlo simulations with different random number generating seeds were performed. Figure 8 (a), (b) and (c) shows the estimated model parameters obtained during each of the Monte-Carlo simulations. The results show that the algorithm is consistent in estimating the model parameters.

Conclusions

The EPS aided VFSA optimization algorithm provides faster convergence and more accurate estimation of model parameters. The algorithm is stable over a reasonable level of signal-to-noise ratio. The uncertainty analysis with Monte-Carlo simulations shows that the algorithm is consistent in estimating the model parameters.

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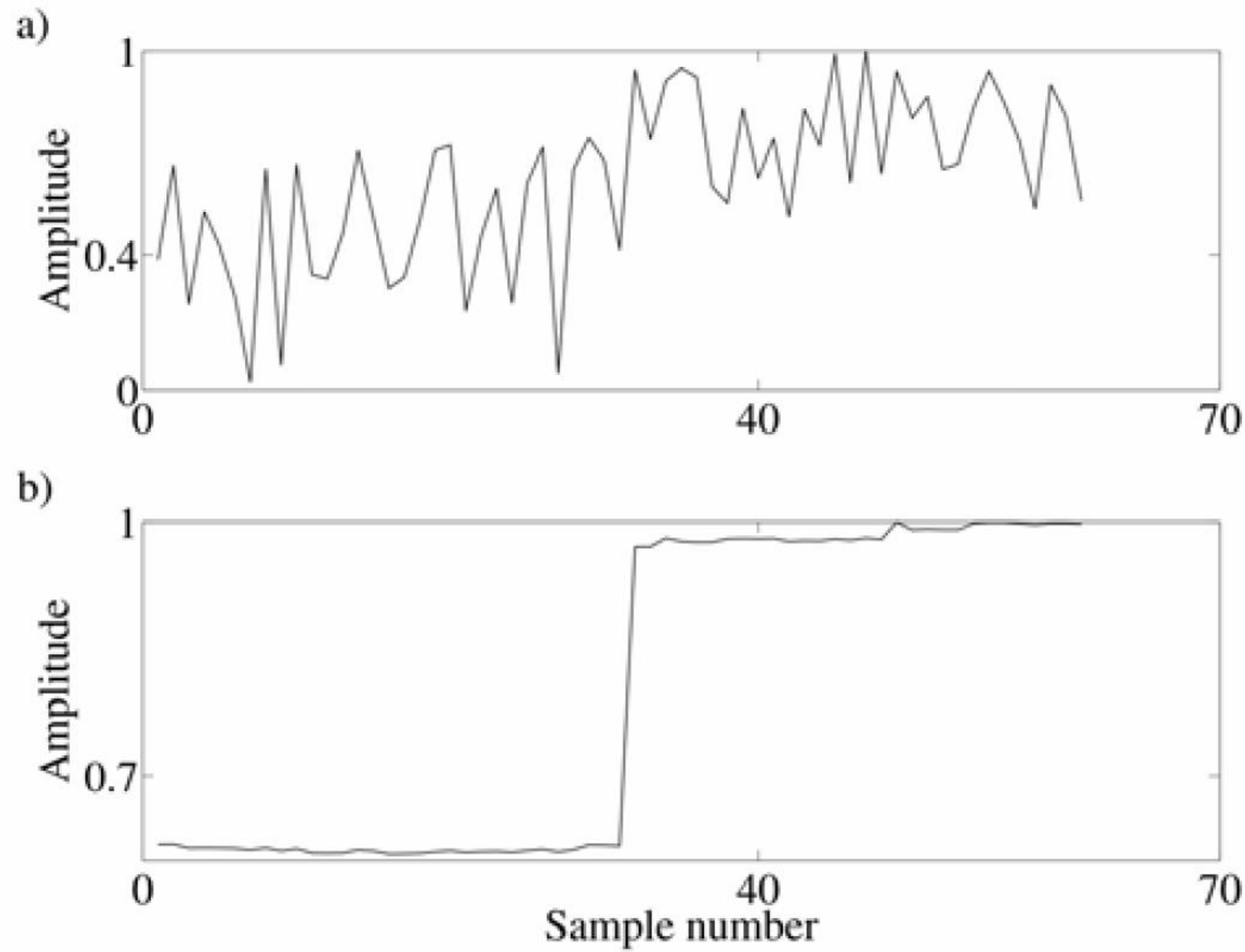

Figure 1. Action of an EPS filter. (a) A particular model vector generated during a VFSA iteration. (b) EPS filtered output. The filtered output shows the previously obscured edge in the model vector.

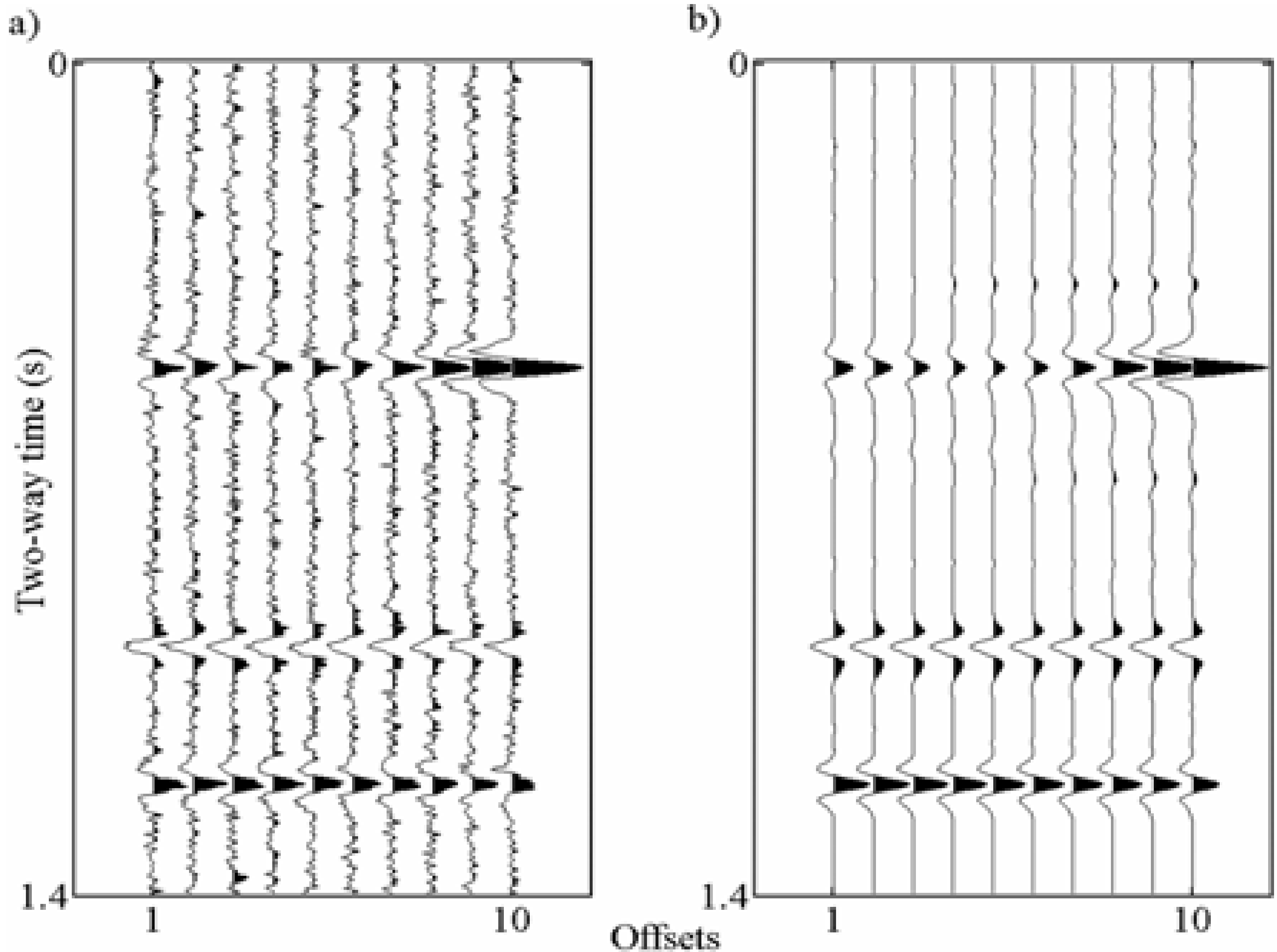

Figure 2. (a) True synthetic data with SNR=20. (b) The estimated data.

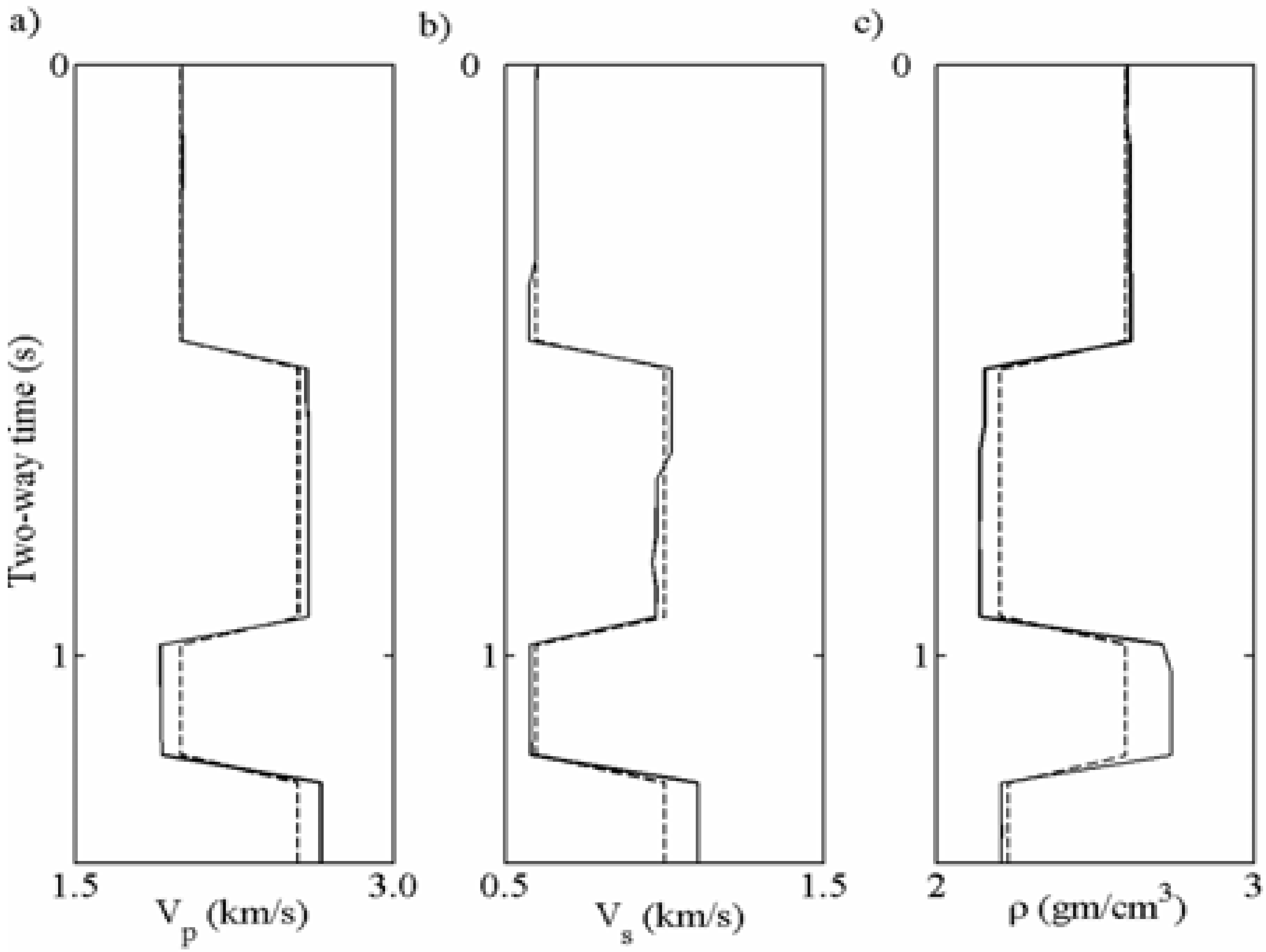

Figure 3. (a) Estimated $\boldsymbol{V_p}$. (b) Estimated $\boldsymbol{V_s}$. (c) Estimated ρ. Dotted and solid lines show true and estimated models respectively.

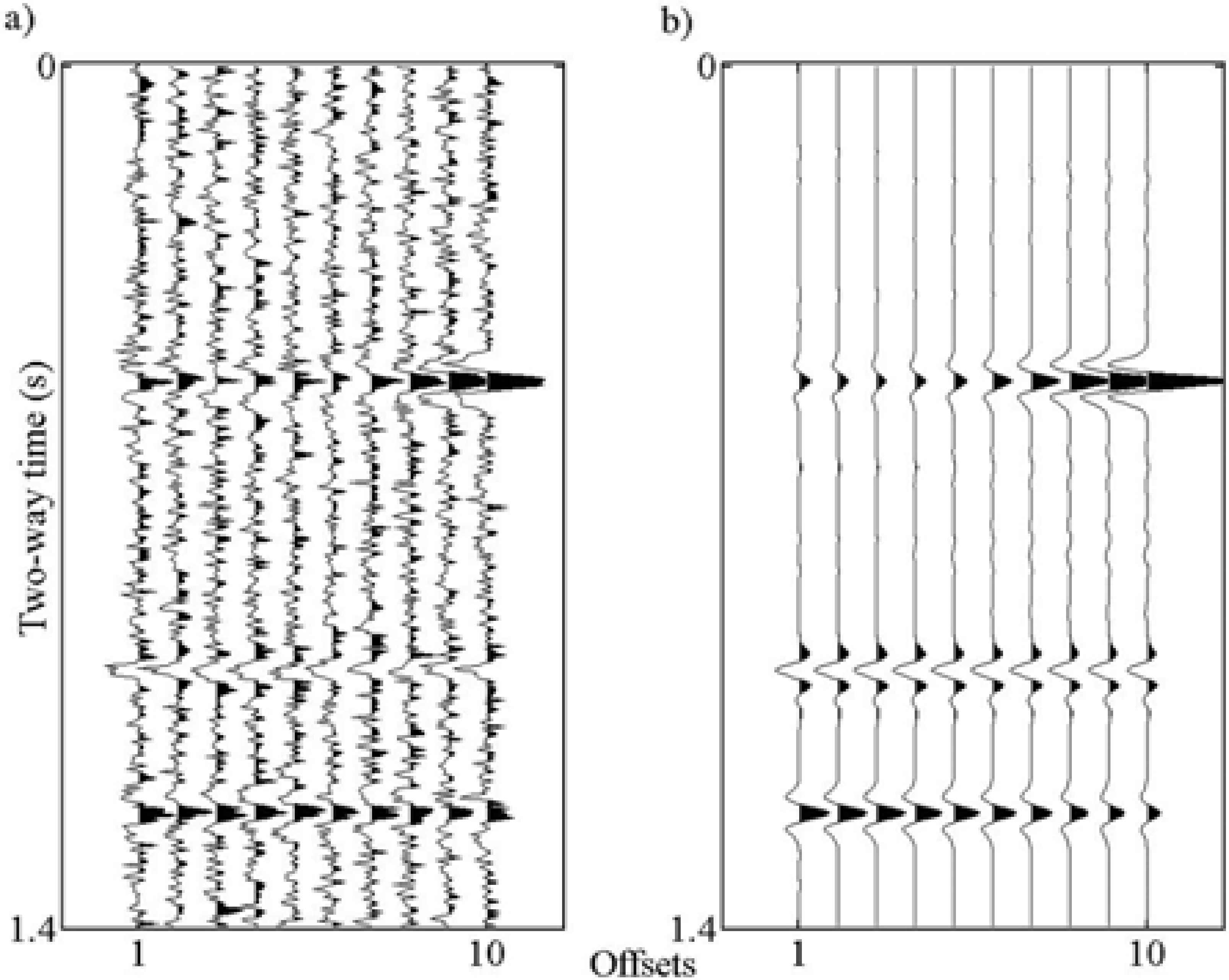

Figure 4. (a) True synthetic data with SNR=10. (b) The estimated data.

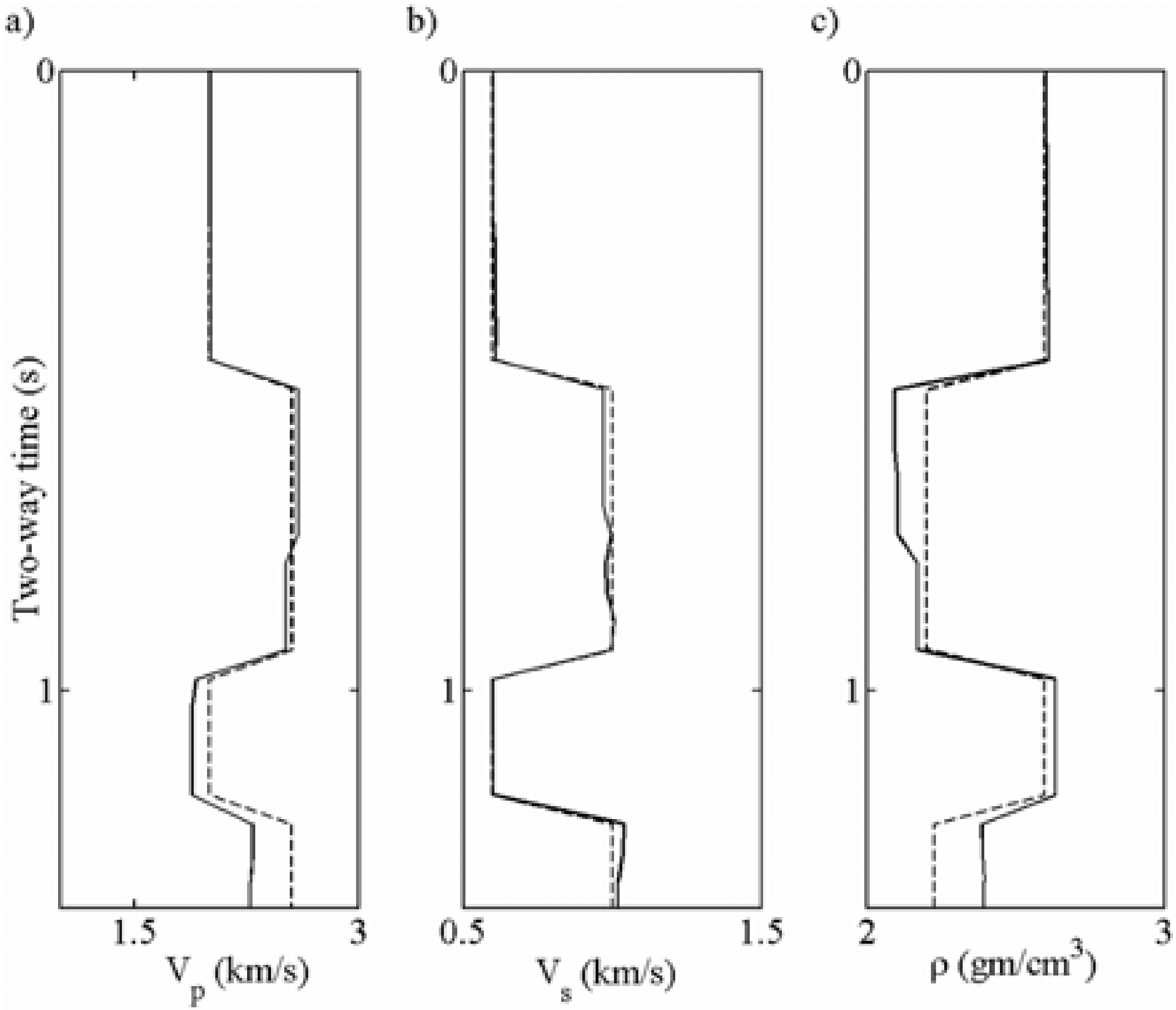

Figure 5. (a) Estimated $\boldsymbol{V_p}$. (b) Estimated $\boldsymbol{V_s}$. (c) Estimated ρ. Dotted and solid lines show true and estimated models respectively.

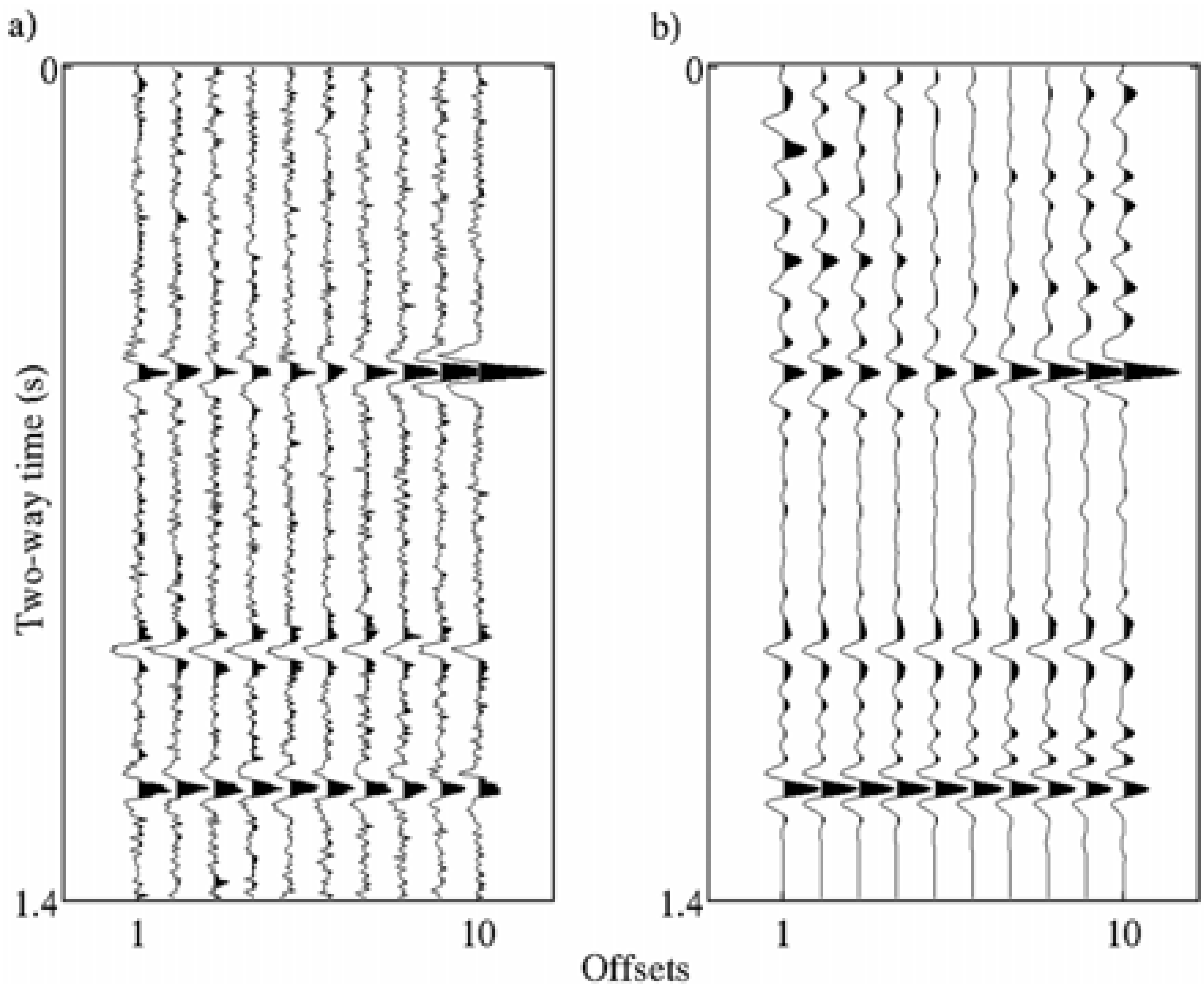

Figure 6. (a) True synthetic data (SNR=20). (b) The estimated data obtained without application of the EPS filters.

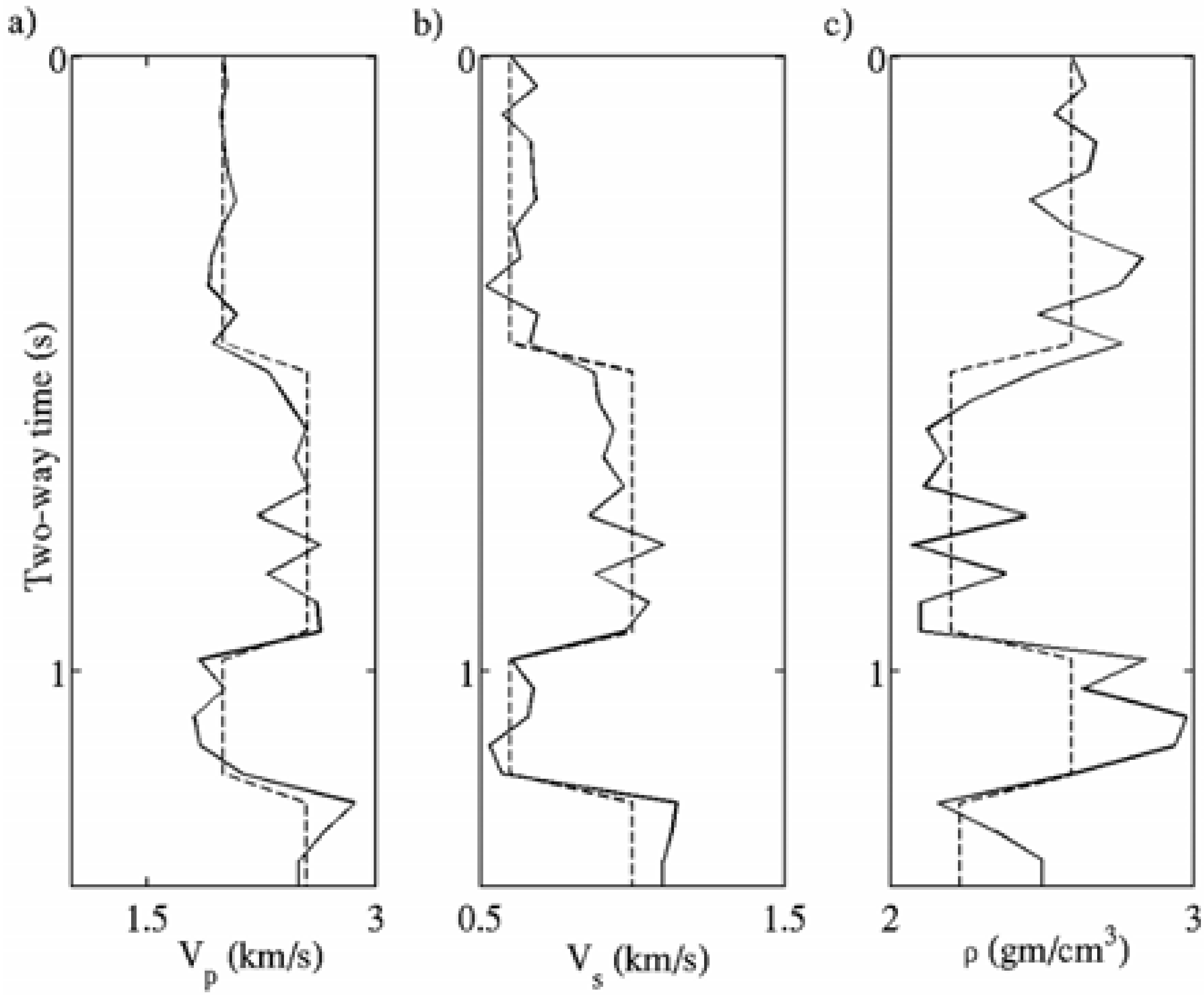

Figure 7. (a) Estimated $\boldsymbol{V_p}$. (b) Estimated $\boldsymbol{V_s}$. (c) Estimated ρ. Dotted and solid lines show true and estimated models respectively.

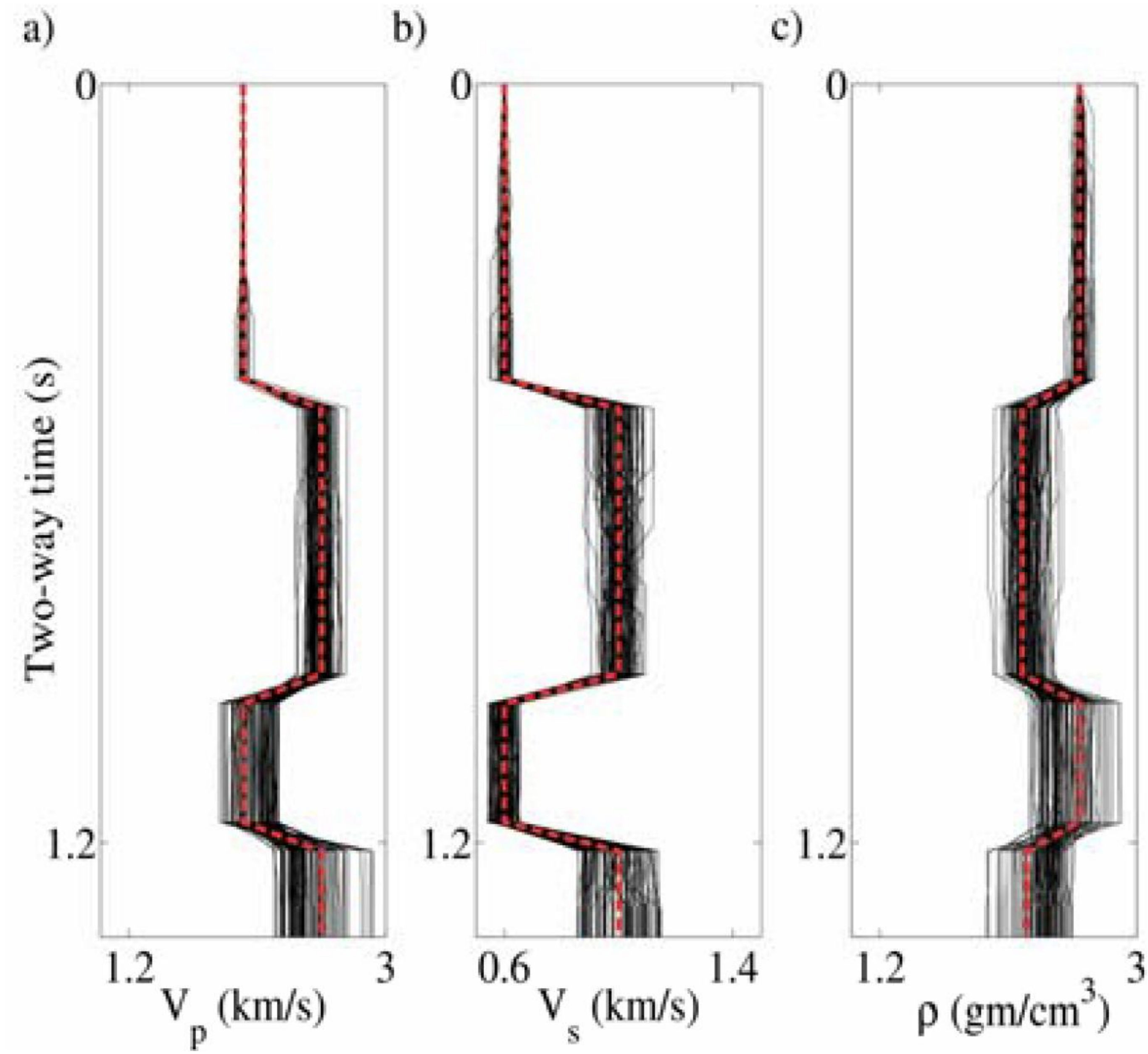

Figure 8. One hundred numbers of Monte-Carlo simulations. (a) Estimations for $\boldsymbol{V}_p$. (b) Estimations for $\boldsymbol{V}_s$. (c) Estimations for ρ. Dotted line represents the true values and solid lines represent the estimated values.