IET Signal Processing

Research Article

Journals
The Institution of
Engineering and Technology

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Reconstruction and basis function construction of electromagnetic interference source signals based on Toeplitz-based singular value decomposition

ISSN 1751-9675
Received on 29th May 2016
Accepted on 28th July 2016
doi: 10.1049/iet-spr.2016.0307
www.ietdl.org

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Abstract: In this study, the authors propose a novel method, namely Toeplitz-based singular value decomposition (or TL-SVD for short) for the reconstruction and basis function construction of electromagnetic interference (EMI) source signals. Given a specific EMI source signal, they first construct a Toeplitz type data matrix. By applying singular value decomposition (SVD) to the constructed matrix, they obtain a set of singular values, which are further divided into two parts, corresponding to the clear and noisy components of input signals, respectively. The de-noised signal can then be reconstructed by reserving relatively larger singular values and abandoning smaller ones. Finally, by utilising the compositions of certain vectors resulting from the previous SVD step, the basis function can be constructed. To evaluate the performance of the proposed method, they conduct extensive experiments on both the synthetic data and real EMI signals, by comparing with several state-of-the-art signal reconstruction methods, such as discrete wavelet transform, EEMD, sparse representation based on K-SVD and OMP. Experimental results demonstrate that the proposed method can outperform comparison approaches.

1 Introduction

Electromagnetic compatibility (EMC) [1–4] has been a popular research topic in recent years. As a main object of EMC study, the analysis of electromagnetic interference (EMI) is of significant importance. Actually, EMI has been an ineluctable part of human life. While in most circumstances, the performance of neighbourhood electronic devices may be deteriorated on account of the existence of EMI. As a consequence, it is critically urgent for exploring the internal construction of EMI sources, such as different categories and special distributions of EMI, which is closely associated with human beings. Therefore, it is necessary to remove noise from original signals, and explore the composition of EMI, implying that there is a compelling need for signal reconstruction and basis function construction.

There have been tremendous amount of existing works on signal reconstruction. The discrete wavelet transform (DWT) [5, 6] is one of the most widely used approaches, together with other variants, such as adaptive wavelets transform [7]. DWT is known to be appropriate for EMI source signal reconstruction on account of its flexibility and self-adaptability, ignoring the non-linearity and non-stability of original signal. Empirical mode decomposition (EMD) [8], a kind of time–frequency analysis method proposed primarily for the decomposition of both non-linear and non-stationary signals, is intuitive, direct, a posteriori and adaptive, with the basis of the decomposition based on, and derived from, the data [9]. Considering existing problems in EMD, such as mode mixing and end effect, EEMD [10] is developed to improve the EMD. Sparse representation [11, 12], rapidly developed in recent years, has been demonstrated to achieve terrific performance in signal reconstruction. In [12], an image denoising method based on K-SVD and OMP, two sparse representation methods, has been presented for its applicability to image signal, which suggests sparse representation has certain superiority in signal denoising. Besides DWT, EEMD and sparse representation, singular value decomposition (SVD) has been applied to numerous literatures involving signal processing frequently in recent years [13–15]. For example, the influence of matrix creation way on signal processing effect of SVD is presented in [16], where SVD is employed in different kind of matrices similar to this work.

Despite not a few works on signal reconstruction, the basis function construction of EMI is still remaining to be a hot issue. Though different approaches, particularly for EMI signal processing, have been developed, few works mention basis function construction. Recently, Wang *et al.* [17] presented an improvement on the characteristic basis function method, while the corresponding theories seem to be imperfect. The non-linear PCA technology mentioned in [18] is also regarded as a feature extraction method, but mainly for blind signal processing, whereas there's less mention of the construction of basis function, which means PCA is not considered in this paper.

For the purpose of realising both the reconstruction and basis function construction of EMI source signals, SVD on Toeplitz matrices, simplified as TL-SVD, is developed in this paper. As a prevailing matrix decomposition method, SVD is famous for its strong convenience. The reason why SVD appears in signal processing quite frequently is that, singular values are known to reflect the energy distribution of useful signal and noise indistinguishable in a certain original signal [19], which adequately signifies SVD can be applied to noise extraction and signal reconstruction. Furthermore, a pair of column vector, separated from two unitary matrices and corresponding to each singular value, can be properly connected to obtain the signal base, according to which the basis function construction can be derived successfully. This work mainly addresses EMI signal reconstruction and basis function construction based on TL-SVD, through transforming EMI source signals to Toeplitz matrices. With the support of some techniques, basis function can be successfully and effectually obtained just by virtue of the specialty of Toeplitz matrices.

Existing works on the theoretical research of signal transforming to matrix are not a few. Generally, transforming signals to Hankel matrices [16] is first taken into account. While there are some discussions on Toeplitz matrix [20, 21], it mainly serves direction of arrival estimation and blind source separation, basically has nothing to do with signal reconstruction and basis function construction. Therefore, a signal reconstruction and basis function construction method, based on TL-SVD, is presented in this paper, with an outstanding performance different from previous theories.

This work provides a reconstruction and basis function construction method based on TL-SVD in virtue of signal transforming to Toeplitz matrix and SVD. The main constructions of this paper lie on three-fold: (i) Taking both advantages of the specific structure of Toeplitz matrices and the superiority of SVD, simplify the process of signal processing. (ii) Denoise the noisy EMI signal through removing its reconstructed part, which is obtained by inverse SVD with remaining specific singular values. (iii) Construct the basis function of EMI utilising the reconstruction results of SVD to Toeplitz matrix transformed from EMI source signal.

The remaining of this paper is organised as follows. In Section 2, we completely present the proposed method, and emphatically introduce corresponding theories with respect to TL-SVD algorithm, together with the mutual correlation coefficient (CCCOEF) and signal-to-noise ratio (SNR), two reconstruction and denoising performance examining approaches. Experimental results are provided in Section 3, where the proposed method is compared with existing state-of-the-art method. Section 4 draws the conclusion of this paper.

2 Signal reconstruction and TL-SVD algorithm

In this section, we will introduce the main thought of the proposed method without any omission, which can be divided into two parts, signal reconstruction and TL-SVD algorithm.

First, employing the inverse SVD, an approximate Toeplitz matrix $\boldsymbol{T}'$, derived from $\boldsymbol{T}$, will be constructed relying on the front q singular values merely. What's more, there exists a critical value q', normally, under which it will reach the best matching to the clear part. Here, we will resort to the distribution diagram of all singular values, in which a significant descent trend will be easily observed. Afterwards, the corresponding reconstructed signal $x'(t)$ will be derived by connecting the first row and first column of T'.

The basis function construction is the second problem, which is required to construct signal bases according to the results of SVD corresponding to front q singular values directly. In this paper, we simply define the ith signal basis as the composition of both the ith column of $\boldsymbol{U}$ and $\boldsymbol{V}$, denoted as U_i and V_i, respectively, without the last item of V_i. For the sake of quantifying the effectiveness of the proposed algorithm, some illustrations of CCCOEF [22, 23] and SNR [24] are described in this section as well serving the experimental part.

2.1 Preprocessing

Provided a random source signal

$$x(t) = (x(t_1), x(t_2), \dots, x(t_N))^{\mathrm{T}},$$

and arranging $x(t_n),\ x(t_{n-1}), \dots, x(t_1)$ and $x(t_n),\ x(t_{n+1}), \dots, x(t_N)$ to be the first line and first column of a Toeplitz matrix, respectively, we will obtain the following Toeplitz matrix:

$$\boldsymbol{T} = \begin{pmatrix} x(t_n) & \cdots & x(t_1) \\ \vdots & \ddots & \vdots \\ x(t_N) & \cdots & x(t_{N-n+1}) \end{pmatrix},$$

where T_{ij}, the ith row and jth column of $\boldsymbol{T}$ ($1 \le i \le N-n+1$, $1 \le j \le n$), is $x(t_{n-j+i})$ actually. According to the source of the elements in T, we call $\boldsymbol{T}$ the source signal matrix naturally. For the convenience of calculation, we simplify it to the following form:

$$\boldsymbol{T} = \begin{pmatrix} x_n & \cdots & x_1 \\ \vdots & \ddots & \vdots \\ x_N & \cdots & x_{N-n+1} \end{pmatrix}.$$

Furthermore, if we denote $m = N - n + 1$, then $\boldsymbol{T}$ is definitely an $m \times n$ matrix.

2.2 Signal reconstruction

Firstly, a specific source signal matrix $\boldsymbol{T} \in \boldsymbol{C}_r^{m\times n}$ can be derived from $x(t)$. The next aim is to obtain decomposition matrices $\boldsymbol{U}$, $\boldsymbol{\Sigma}$, $\boldsymbol{V}$ resulted from SVD, where $\Sigma = \mathrm{diag}(\sigma_1, \dots, \sigma_r)$, and $\sigma_i (i = 1, \dots, r)$ are non-zero singular values of Tsatisfying

$$\sigma_1 \ge \cdots \ge \sigma_r > 0.$$

A great deal of researches [16, 25] indicates only a few singular values will achieve relatively large values, implying that a small number of singular values contain as much information of original signal as possible, which should be taken into consider in the next stage. Thus, we only select q singular values

$$\sigma_1, \dots, \sigma_q$$

assumed reflecting the information of clear signal. In order to decrease interfering of complex situations when there's a fuzzy boundary of q, a further assumption of the selected singular values is

$$\frac{\sum_{i=1}^{q} \sigma_i}{\sum_{i=1}^{r} \sigma_i} \le \varepsilon,$$

where ε is the threshold value to limit the selection of singular value. Then we can obtain the approximate Toeplitz matrix

$$\boldsymbol{T}' = \boldsymbol{U} \begin{pmatrix} \Sigma' & 0 \\ 0 & 0 \end{pmatrix} V^{\mathrm{H}},$$

where $\Sigma' = \mathrm{diag}(\sigma_1, \sigma_2, \dots, \sigma_q)$, which will be recovered to the reconstructed signal via Toeplitz matrix transforming to signal.

2.3 Basis function construction

In this subsection, we provide another essential part of the proposed method, the construction idea of basis function. Let

$$\boldsymbol{U} = (U_1, U_2), \quad \boldsymbol{V} = (V_1, V_2), \quad \Sigma' = \mathrm{diag}(\sigma_1, \dots, \sigma_q),$$

where

$$U_1 \in \boldsymbol{C}^{m\times q}, \quad U_2 \in \boldsymbol{C}^{m\times (m-q)}, \quad V_1 \in \boldsymbol{C}^{n\times q}, \quad V_2 \in \boldsymbol{C}^{n\times (n-q)},$$

then the SVD of $\boldsymbol{T}'$ can be expressed as

$$\boldsymbol{T}' = (U_1, U_2) \begin{pmatrix} \Sigma' & \\ & 0 \end{pmatrix} \begin{pmatrix} V_1^{\mathrm{H}} \\ V_2^{\mathrm{H}} \end{pmatrix} = (U_1 \Sigma', 0) \begin{pmatrix} V_1^{\mathrm{H}} \\ V_2^{\mathrm{H}} \end{pmatrix} = U_1 \Sigma' V_1^{\mathrm{H}},$$

where $U_1 = (u_1, \dots, u_q)$ and $V_1 = (v_1, \dots, v_q)$. It is not difficult to expand the last item and obtain the further decomposition

$$\boldsymbol{T}' = U_1 \Sigma' V_1^{\mathrm{H}} = \sigma_1 u_1 v_1^{\mathrm{H}} + \cdots + \sigma_q u_q v_q^{\mathrm{H}}.$$

How to acquire signal bases is the second problem demanding prompt solution. Its worth noting that each pair of u_i and v_i determines a signal basis, denoted by $\hat{x}_i (i = 1, 2, \dots, q)$ might as well. We can directly obtain the signal basis $\hat{x}_i$ through connecting v_i to the end of u_i (without the last item). As a matter of fact, the construction idea of the ith signal basis is just needs to put u_i (without the last item) and v_i together, which is proved to be an advisable choice according to the results of comparison experiments. The combination of $\hat{x}_i (i = 1, 2, \dots, q)$ is the exact

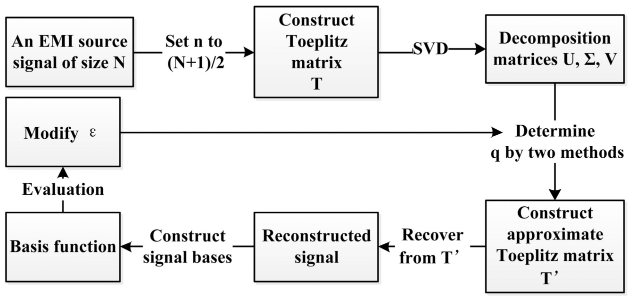


Fig. 1 *Basic procedure of TL-SVD algorithm*

basis function we seek for, signifying we have finished the construction of basis function.

2.4 TL-SVD algorithm

At first, we present two indispensable assumptions for the selection of n, the dimension of source signal matrices, and the threshold value ε.

i. In order to reduce the calculation, we set n to $((N+1)/2)$ if n is odd, and $(N/2)+1$, otherwise.
ii. In order to avoid losing much original information, we set ε in interval [0.1, 0.7] under normal circumstances, while it depends on the experimental results.

Given an source signal of size N, the basic procedure of TL-SVD algorithm can be formulated as follows:

Step 1: Set n to $N/2+1$, and construct the corresponding Toeplitz matrix $\boldsymbol{T}$.
Step 2: Perform SVD on $\boldsymbol{T}$ to obtain decomposition matrices $\boldsymbol{\Sigma}$, $\boldsymbol{U}$ and $\boldsymbol{V}$.
Step 3: Determine the maximum q satisfying $\left(\sum_{i=1}^{q}\sigma_i / \sum_{i=1}^{r}\sigma_i\right) \leq \varepsilon$, or resorting to the distribution of all singular values, and construct approximate Toeplitz matrix$\boldsymbol{T}'$ utilising front q singular values.
Step 4: Recover the reconstructed signal by connecting the first row and first column of $\boldsymbol{T}'$.
Step 5: Construct signal bases $\hat{x}_i(i=1,2,\ldots,q)$ with the connection of u_i and v_i.
Step 6: Combine $\hat{x}_i(i=1,2,\ldots,q)$ to a basis function of the corresponding source signal.
Step 7: Evaluate the reconstruction effectiveness in appropriate assessment approaches.
Step 8: If the evaluation result meets the satisfactory effectiveness, output the final recovered signal. Otherwise, update q (modify the threshold value) and go back to Step 3.

The basic procedure of our method is shown in Fig. 1 for a clearer comprehension of the proposed approach, where N is considered to be odd without loss of generality.

2.5 Cross-correlation coefficient

CCCOEF (cross-correlation coefficient) assessment [24] is a prevailing approach, which often reflects the similarity between the reconstructed signal and theoretical reference signal depending on the following parameter:

$$R = \frac{\mathrm{Cov}(x,y)}{\sigma_x \sigma_y},$$

where y is the recovered signal from x, $\mathrm{Cov}(x,y)$ represents the covariance of x and y, and σ_x and σ_y refer to the standard deviations of x and y, respectively. In most instances, a larger CCCOEF indicate higher similarity between the contrastive two signals, which reflects excellent matching capability of the corresponding method.

2.6 Signal-to-noise ratio

SNR is a traditional and widely applicable method basically for noise measurement, which is used to be an evaluation standard of the reconstruction quality. Generally speaking, SNR is a measure frequently occurring in science and engineering that compares the level of a desired signal to the level of background noise, which is routinely defined as the ratio of clear signal power to the noise power as follows:

$$\mathrm{SNR} = 10\lg\left(\frac{P_\mathrm{s}}{P_\mathrm{n}}\right),$$

where P_s and P_n represent the powers of clear and noise signals, respectively, satisfying

$$P_\mathrm{s} = \frac{1}{N}\sum_{i=1}^{N} x_i^2 \quad \text{and} \quad P_\mathrm{n} = \frac{1}{N}\sum_{i=1}^{N} \tilde{x}_i^2,$$

where x_i and $\tilde{x}_i$ are the ith components corresponding to the clear and noise signals, respectively. In most cases, a relatively higher SNR often indicates a better denosing performance, also implying better reconstruction effectiveness.

3 Numerical experiment

To evaluate the effectiveness and applicability of the proposed algorithm, experiments both on synthetic and real noisy signals compared with state-of-the-art approaches are provided in this section. In the first part, comparison experiments on a synthetic noisy signal are presented to verify the validity of the proposed method, where we critically take EEMD, DWT and SPKO into consider with rigorous analyses. In the second part, a real EMI noisy signal is both for signal reconstruction and basis function construction, in order to evaluate the applicability of the proposed method.

3.1 Experiments on synthetic noisy signal

We select the following synthetic noisy signal:

$$x(t) = x_1 t + n(t)$$

as our test signal, where

$$x_1(t) = \sin t + 2\sin 3t + 3\sin 7t (t = 0, 0.01, \ldots, 6),$$

and $n(t)$ is a random white noise. The synthetic noisy signal is shown in Figs. 2*a–c* with its two components, where x and y label
Q2 represent time (s) and amplitude (mV), respectively. We intend to implement the proposed algorithm on $x(t)$.

Fig. 3 exhibits the distribution of all singular values in sequence, where a sharp drop can be observed obviously. According to what is shows in Fig. 3, we can preliminary judge the optimal choice of q is in the range of 5–10. Furthermore, Table 1

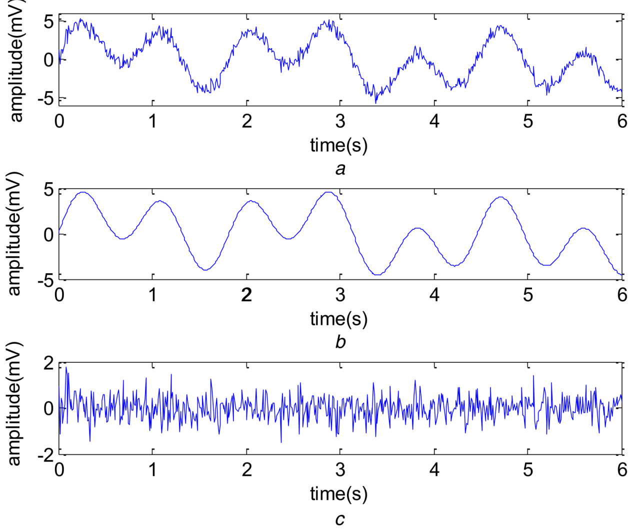


Fig. 2 *Synthetic noisy signal with two composition items*
(a) Synthetic noisy signal $x(t)$, ***(b)*** Clear signal x_1t, ***(c)*** Noise signal $n(t)$

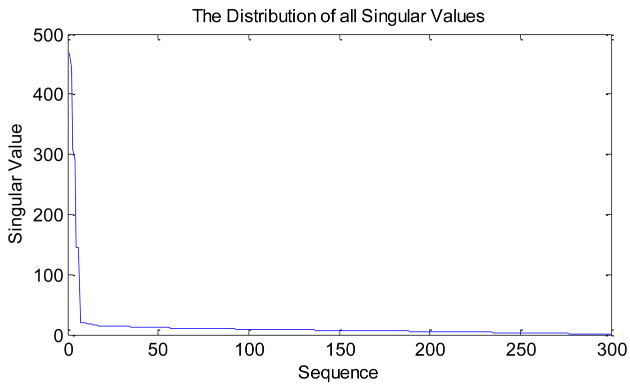
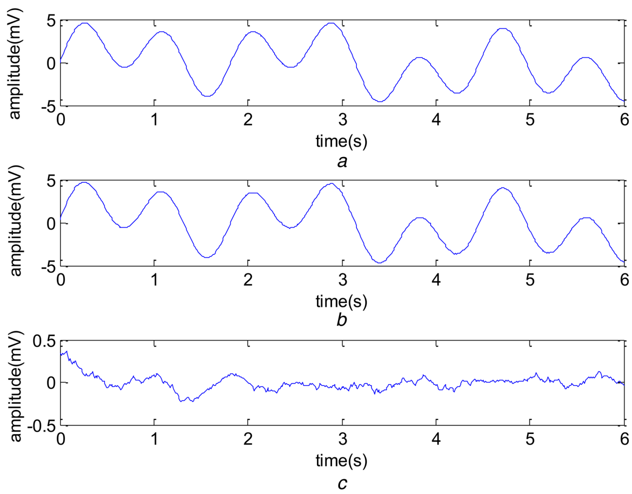


Fig. 3 *Distribution of all singular values generated by the Toeplitz matrix corresponding to synthetic noisy signal $x(t)$ when applied TL-SVD algorithm*



Q4 **Fig. 4** *Residual between the optimal recovered signal $x_2(t)$and $x_1(t)$*
(a) Clear signal $x_1(t)$, ***(b)*** Recovered signal $x_2(t)$ based on TL-SVD when setting the q to 6, the optimal choice, ***(c)*** Difference $x_2(t) - x_1(t)$, namely residual between $x_2(t)$ and $x_1(t)$

records CCCOEFs and SNRs corresponding to different threshold values (0.41, 0.43, 0.45, 0.47, 0.49 and 0.51), from which we can assert $q = 6$ is the optimal choice. Figs. 4*a*–*c* also presents the residual between the optimal recovered signals $x_2(t)$ and $x_1(t)$, which demonstrates a fairly high recovery rate of the proposed algorithm. Figs. 5*a* and *b*, respectively, show the recovered signal and noise based on TL-SVD algorithm under the optimal threshold value, namely the optimal choice of q. As comparison, Figs. 5*c*–*h*, respectively, show the recovered signals and noise based on EEMD, DWT (soft threshold value) and SPKO. For a more intuitive explanation towards the results, Table 2 displays CCCOEFs, SNRs and running time of the proposed method, EEMD, DWT and SPKO.

The results of CCCOEFs and SNRs shown in Table 1 both present a noticeable trend of rise first then fall, implying reconstruction performance of the proposed algorithm is influenced by the selection of singular values. While results may be worse when q substantially deviates the optimal value, the proposed

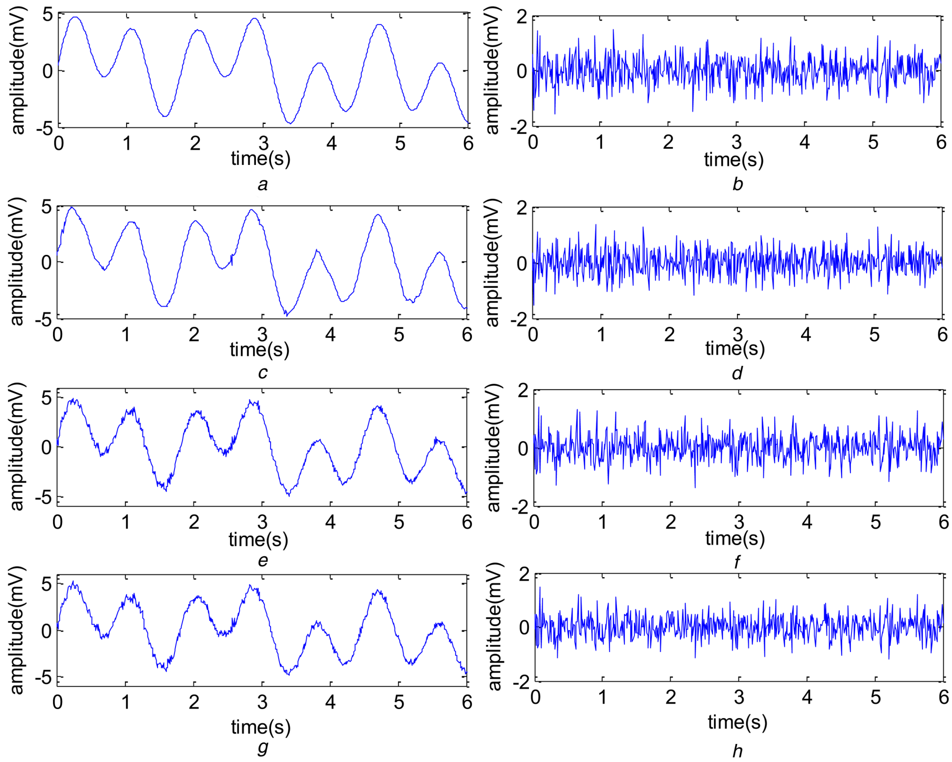


Fig. 5 *Recovered signal and noise based on TL-SVD algorithm under the optimal threshold value*
(a) Recovered signal based on TL-SVD algorithm under the optimal threshold value, ***(b)*** Noise corresponding to the recovered signal based on TL-SVD algorithm under the optimal threshold value, ***(c)*** Recovered signal based on DWT, ***(d)*** Noise corresponding to the recovered signal based on DWT, ***(e)*** Recovered signal based on EEMD, ***(f)*** Noise corresponding to the recovered signal based on EEMD, ***(g)*** Recovered signal based on SPKO, ***(h)*** Noise corresponding to the recovered signal based on SPKO

method can achieve ideal effect nearby the optimal choice of q. Table 2 also convinces us that our method reaches more superior results, both reflected in SNRs and CCCOEFs, though the running time is a little longer than DWT. Without exception, Figs. 4 and 5 both reveal strong recoveries from the perspective of residual and recovered signal. Particularly, in Fig. 5, there are distinct superiorities of the proposed method in the smoothness of the reconstructed signal, indicating an extremely high reducibility.

3.2 Experiments on real EMI source signal

Experiments on a real EMI source signal carrying uncertain noise are displayed in this section. What Fig. 7*a* shows is a real EMI source signal $y(t)$ of length 2001, which is an EEG noisy signal taken from the EEG signal database provided in [26]. We intend to apply TL-SVD algorithm to this EEG noisy signal both for signal reconstruction and basis function construction, which needs us to analysis the distribution of singular values first. Fig. 6 shows the distribution of front 100 singular values, from which it is difficult to determine the optimal choice of q. While it is not extremely noticeable, there is still a sharp descent when the distribution curve passes 40. Thus we take $q = 40$ as the optimal choice without loss of generality.

What calls for special attention is that SNR and CCCOEF both fail to evaluate the effectiveness of the proposed method on account of the unavailability of clear signal. As a consequence, we verify the proposed method only compared with DWT, which performs relatively well in previous comparison experiments. Figs. 7*b* and *c* show the recovered signal based on TL-SVD algorithm ($q = 40$) and DWT (soft threshold value), respectively. In the end, Figs. 8*a–j* exhibit a portion of basis function generated by the front ten singular values arranged from (a)–(j).

In Fig. 7, although there is no exact data to figure out which is the better, what Fig. 7*b* shows is definitely faultless when compared with Fig. 7*c*, implying the proposed method performs fairly outstanding in signal reconstruction. Furthermore, it's noticeable that each signal basis in Fig. 8 has extremely smooth and continuous properties and distributes according to some specific variation regulations.

Therefore, combining the results of Section 3.1 with this part, we can draw corresponding conclusions. Our algorithm is demonstrated to be in a superior position from above analyses, and it is indeed applicable to the signal reconstruction and basis function construction problem. Experiments, compared with state-of-the-art methods for signal reconstruction, also suggest its superiority and strong applicability for EMI source signals. To summarise, in some applications under the context of EMI, the proposed algorithm satisfies the basic requirements of signal reconstruction and basis function construction to a large extent.

Table 1 CCCOEFs and SNRs under different threshold values based on TL-SVD algorithms

Threshold values	0.41 ($q = 5$)	0.43 ($q = 6$)	0.45 ($q = 6$)	0.47 ($q = 10$)	0.49 ($q = 14$)	0.51 ($q = 19$)
CCCOEF	0.9781	29.6036	29.6036	0.9983	0.9977	0.9963
SNR	13.6125	0.9995	0.9995	24.5485	23.2016	21.2354

Table 2 CCCOEF, SNR and running time of all method when reconstructing the synthetic signal $x(t)$

Method	TL-SVD ($q = 6$)	DWT (soft threshold value)	EEMD	SPKO
CCCOEF	0.9995	0.9979	0.9962	0.9445
SNR	29.6036	23.5444	21.0943	17.6742
running time (s)	0.064169	0.011501	2.036011	2.45073

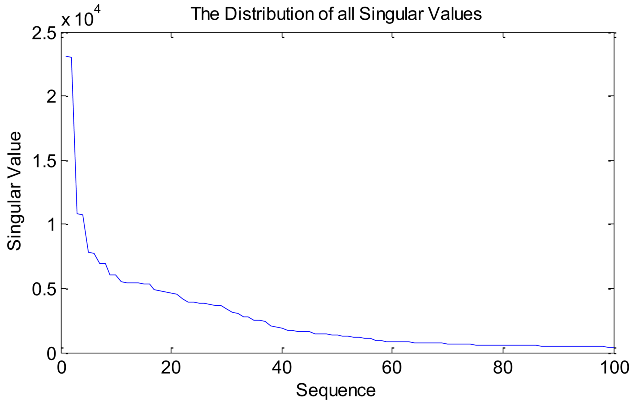


Fig. 6 *Distribution of front 100 singular values generated by the Toeplitz matrix corresponding to EEG noisy signal* $y(t)$ *applied TL-SVD algorithm*

4 Conclusion

In this paper, we proposed a signal reconstruction and basis function construction algorithm, denoted as TL-SVD, in allusion to EMI source signals. What is novelty and particularity of the proposed algorithm rests with it making full use of the specific structure of Toeplitz matrices together with the flexibility of SVD to simplify the procedure of signal reconstruction considerably. We also successfully addressed the basis function construction problem for EMI, through utilising the decomposition matrices resulting from specific SVD. As an all-around signal reconstruction and basis function construction algorithm, it's sufficient to apply it to EMI source signals with remarkable effectiveness. It was further proved our algorithm has superior reconstruction performance compared with DWT, EEMD and SPKO, three popular methods.

It is worthy of notice that the basis function construction thought, the important part of the proposed method, is based on an assumption which has not been proved in this paper, though it is comparatively reasonable from the experimental analyses. Hence, it is necessary to seek for more logical ideas for the basis function construction of EMI.

5 Acknowledgments

This work was supported by the National Natural and Science Foundation of China (grant no. 61379001).

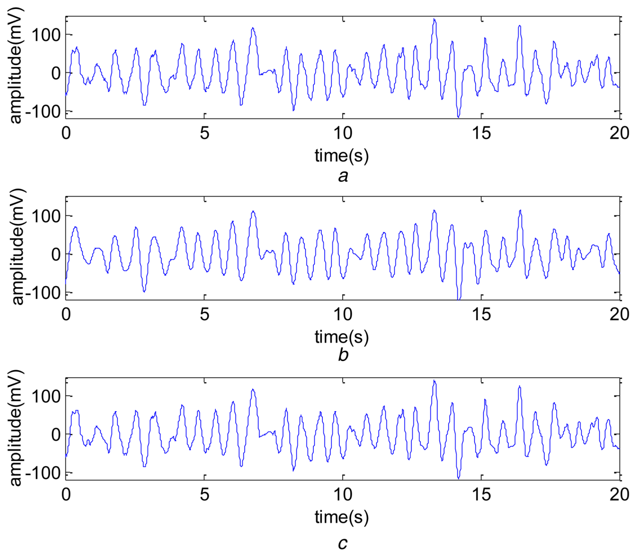


Fig. 7 *Recovered signal based on TL-SVD algorithm*
(a) Original EEG noisy signal $y(t)$, ***(b)*** Recovered signal based on TL-SVD algorithm under the optimal threshold value, ***(c)*** Recovered signal based on DWT with soft threshold value

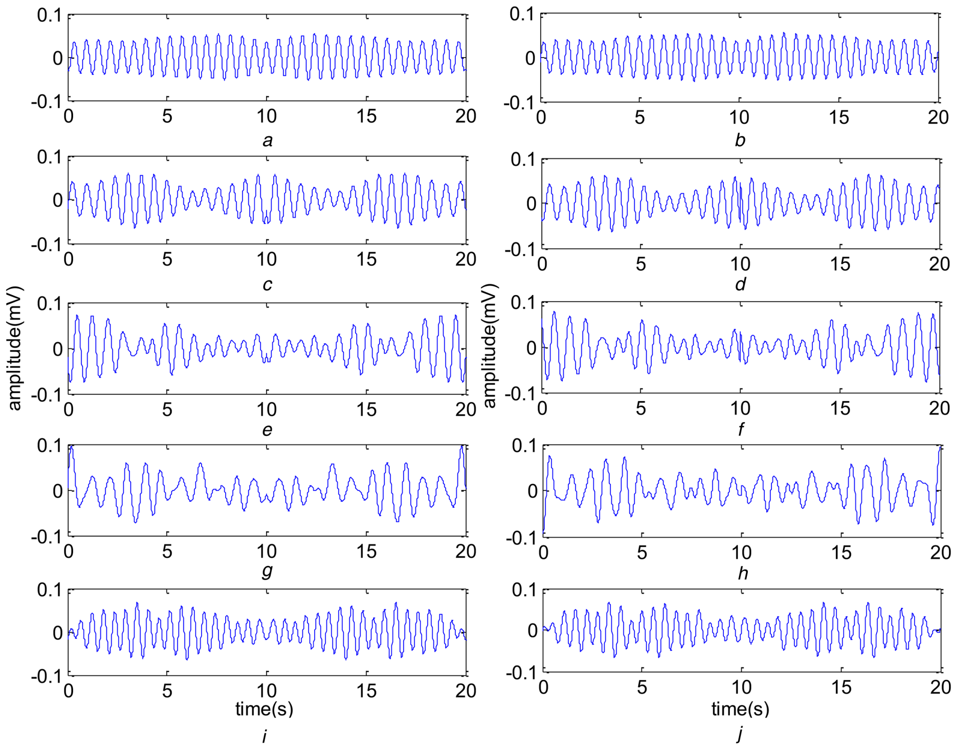


Fig. 8 *Basis function only generated by the front ten singular values arranged from (a)–(j) in the sequence of singular value arrangement. (a) Belonging to the largest singular value. (j) Belonging to the tenth singular value. The rest is the same to (a) and (j) distributed between (a) and (j)*

6 References

[1] Salameh, M.S.A., Zuraiqi, E.T.A.: 'Solutions to electromagnetic compatibility problems using artificial neural networks representation of vector finite element method', *IET Microw. Antennas Propag.*, 2008, **2**, (4), pp. 348–357

[2] Li, H.Y., Fu, Y., Zhao, D.: 'Identification of power quality disturbances based on FFT and attribute weighted artificial immune evolutionary classifier', *Appl. Mech. Mater.*, 2014, **530-531**, pp. 277–280

[3] Zhao, D., Lu, H., Li, H.: 'An ICA and AIS based method for electromagnetic compatibility analysis', *Adv. Mater. Res.*, 2013, **846-847**, pp. 547–550

[4] Li, H., Wang, C., Zhao, D.: 'An improved EMD and its applications to find the basis functions of EMI signals', *Math. Probl. Eng.*, 2015, Article ID 150127

Q3 [5] Masselos, K., Andreopoulos, Y., Stouraitis, T.: 'Performance comparison of two-dimensional discrete wavelet transform computation schedules on a VLIW digital signal processor'. IEE Proc. - Vision Image and Signal Processing, 2006, vol. 153, no. 2, pp. 173–180

[6] Frangakis, A.S., Stoschek, A., Hegerl, R.: 'Wavelet transform filtering and nonlinear anisotropic diffusion assessed for signal reconstruction performance on multidimensional biomedical data', *IEEE Trans. Biomed. Eng.*, 2001, **48**, (2), pp. 213–222

[7] Kadambe, S., Srinivasan, P.: 'Adaptive wavelets for signal classification and compression', *AEU – Int. J. Electron. Commun.*, 2006, **60**, (1), pp. 45–55

[8] Prince, A., Senroy, N., Balasubramanian, R.: 'Targeted approach to apply masking signal-based empirical mode decomposition for mode identification from dynamic power system wide area measurement signal data', *IET Gener. Transm. Distrib.*, 2011, **5**, (10), pp. 1025–1032

[9] Huang, N.E., Shen, Z., Long, S.R.: 'The empirical mode decomposition and the Hilbert spectrum for nonlinear and non-stationary time series analysis'. Proc. of the Royal Society of London A: Mathematical, Physical and Engineering Sciences. The Royal Society, 1998, vol. **454, no**. 1971, pp. 903–995

[10] Wang, C., Li, H., Xiang, W., *et al.*: 'A new signal classification method based on EEMD and FCM and its application in bearing fault diagnosis', *Appl. Mech. Mater.*, 2014, **602-605**, pp. 1803–1806

[11] Aharon, M., Elad, M., Bruckstein, A.K.: 'K-SVD: an algorithm for designing overcomplete dictionaries for sparse representation', *IEEE Trans. Signal Process.*, 2006, **54**, (11), pp. 4311–4322

[12] Chen, C., Zhang, S., Chen, Y.: 'An image denoising method based on OMP and K-SVD', *Int. J. Adv. Comput. Technol.*, 2012, **4**, (4), pp. 32–40

[13] Chen, J., Zhang, Z., Wang, Y.: 'Relevance metric learning for person re-identification by exploiting list wise similarities', *IEEE Trans. Image Process.*, 2015, **24**, (12), pp. 1657–1662

[14] Chen, J., Wang, Y., Tang, Y.Y.: 'Person re-identification by exploiting spatio-temporal cues and multi-view metric learning', *IEEE Signal Process. Lett.*, 2016, **23**, (7), pp. 998–1002

[15] Zhao, D., Li, H.: 'On the computation of inverses and determinants of a kind of special matrices', *Appl. Math. Comput.*, 2010, **250**, pp. 721–726

[16] Zhao, X., Ye, B., Chen, T.: '*Influence of matrix creation way on signal processing effect of singular value decomposition*' (Journal of South China University of Technology, 2008)

[17] Wang, Q., Wang, W., Liu, Z.: 'Analysis of electromagnetic scattering by using modified characteristic basis function method', *Syst. Eng. Electron.*, 2010, **32**, (10), pp. 2103–2106

[18] Shao, R., Hu, W., Wang, Y.: 'The fault feature extraction and classification of gear using principal component analysis and kernel principal component analysis based on the wavelet packet transform', *Measurement*, 2014, **54**, (6), pp. 118–132

[19] Kakarala, R., Ogunbona, P.O.: 'Signal analysis using a multiresolution form of the singular value decomposition', *IEEE Trans. Image Process.*, 2001, **10**, (5), pp. 724–735

[20] Vallet, P., Loubaton, P.: 'Toeplitz rectification and DOA estimation with music'. IEEE Int. Conf. on Acoustics, Speech and Signal Processing (ICASSP), 2014, 2014, pp. 2237–2241

[21] Ma, H.G., Jiang, Q.B., Liu, Z.Q., *et al.*: 'A novel blind source separation method for single-channel signal', *Signal Process.*, 2010, **90**, (12), pp. 3232–3241

[22] Pu, Y., Xu, Q., Wang, W.: 'Image change detection based on cross-correlation coefficient by using genetic algorithm'. First Int. Conf. on Agro-Geoinformatics (Agro-Geoinformatics), 2012, 2012, pp. 1–5

[23] Tanaka, T., Ueda, K., Satou, K.: 'A novel detection method of active and reactive currents in single-phase circuits using the correlation and cross-correlation coefficients and its applications'. Industry Applications Conf., 2004. 39th IAS Annual Meeting. Conf. Record of the 2004 IEEE, 2004, vol. **l. 2**, pp. 836–842

[24] Najafipour, A., Babaee, A., Shahrtash, S.M.: 'Comparing the trustworthiness of signal-to-noise ratio and peak signal-to-noise ratio in processing noisy partial discharge signals', *IET Sci. Measure. Technol.*, 2013, **7**, (2), pp. 112–118

[25] Lu, J., Zhao, Y.: 'Dominant singular value decomposition representation for face recognition', *Signal Process.*, 2010, **90**, (6), pp. 2087–2093

[26] Andrzejak, R.G., Schindler, K., Rummel, C.: 'Nonrandomness, nonlinear dependence, and nonstationary of electroencephalographic recordings from epilepsy patients', *Phys. Rev. E Stat. Nonlinear Soft Matter Phys.*, 2012, **86**, (4), pp. 2745–2756

IET-SPR20160307

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