Deep Learning-Based Automatic Blind Identification Procedure for Structural Modal Identification

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ABSTRACT

Traditional modal identification approaches require too much user interaction, which results in low implementation efficiency. This study develops an automatic approach that combines deep learning and blind source separation to determine the modal parameters of structures. The core object of the proposed approach is to establish a multi-task deep neural network (MTDNN) that enables it to automatically obtain independent modes from multi-mode vibration responses of structures. Then modal frequencies and damping ratios of structures can be extracted from independent modes by employing the traditional random decrement technique and curve fitting approach. The weights between the last two layers of MTDNN represent the corresponding mode shapes. The approach is implemented in a long-span cable-stayed bridge in engineering practice for validation. For the field test, five accelerometers are employed to derive acceleration responses of the structure. The results indicate the ability of the proposed approach to automatically determine the modal parameters of structures with reliable accuracy, which provides a promising new solution for online modal parameter identification and modal tracking of structures.

INTRODUCTION

The identification of modal parameters (i.e., modal frequencies, mode shapes, and damping ratios) of long-span bridges is important for structural health monitoring (SHM) because modal parameters are the inherent characteristics that can reflect the status of a structure. It has been validated that damages that happened to a structure will result in the change of modal parameters [1], therefore, to ensure structural safety, it's of great necessity to identify modal parameters accurately and rapidly to facilitate structural damage detection.

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At present, the input-output and output-only test-based approaches are the two main algorithms for modal parameter identification. The former method requires external input data which is difficult to obtain, thus, its application is limited. On the contrary, the output-only test-based approach, also named as operational modal analysis (OMA) approach, only relies on structural output data. this advantage has made it become the most prevailing method. However, the traditional OMA approaches don't have the ability for continuous monitoring since it requires user intervention. Recently, many tries have been done to automate existing OMA approaches through different clustering techniques. For example, Zhang et al. [2] and Sun et al. [3] automate the identification process utilizing fast density peaks clustering algorithm and hierarchical clustering techniques, respectively. However, those methods only partially automate the modal parameters identification process, since they still depend on several user-defined parameters, thus, require user interaction.

It's well-known that deep learning technique has a significant ability to learn features and establish a relationship from mass data. However, fewer studies were found applying it for automated modal parameter identification. One represented work done by Liu et al. [4] developed a machine-learning-based modal identification approach based on the uncorrelation and non-Gaussianity characteristic of modal responses. Experiments showed that the developed neural network has good modal identification accuracy similar to that of OMA approaches but in a fully automated manner.

Inspired by the above research, this study developed a novel automatic modal identification approach based on deep learning. The approach initially uses the sparse component analysis (SCA) technique to construct datasets based on multi-mode vibration responses and independent modal responses of structures. Then, a multi-task deep neural network (MTDNN) was established to automatically decompose structural multi-mode responses. Subsequently, structural modal parameters are determined from the output of MTDNN by using the random decrement technique (RDT) and curve fitting approach. The developed approach does not require any user intervention but with high computational efficiency and accuracy.

METHODOLOGY

As illustrated in Figure 1, the proposed automatic modal identification approach involves three parts: (1) multi-mode vibration responses decomposition by SCA approach for data set preparation; (2) MTDNN development, training, and prediction. The source signals and corresponding independent modal responses are treated as inputs and outputs of MTDNN, which aims to enforce MTDNN to be captive to separate the modes; (3) implementation of RDT and curve fitting approach to identify modal frequencies and damping ratios. Additionally, in the second step, the last layer of MTDNN was used to reconstruct the input. Thus, the weights between the penultimate and final layers of the MTDNN represent the mode shapes of structures.

Data Preparation using SCA

The purpose of SCA is to separate independent modal sources from origin structural responses for data sets preparation [5]. As shown in Figure 2, the short-time Fourier transform (STFT) was first implemented to transform source signal $\boldsymbol{X}(t)$ into time-frequency (TF) domain X(ξ). Then the mixing matrix $\boldsymbol{A}$ and source signal reconstruction were successively implemented. The single source points (SSP) detection algorithm [6] and fuzzy c-means clustering algorithm were employed in the former part, and the STFT inverse transform was performed in the later part.

In the above illustration, $\boldsymbol{X}(t)$ can represent the acceleration, velocity, or displacement responses of a structure. Each independent modal response obtained through SCA can be treated as outputs of the neural network. Therefore, as the SCA provides enough data samples, the deep neural network will learn the relationship between source signals and independent modal responses, and thus act similarly to SCA.

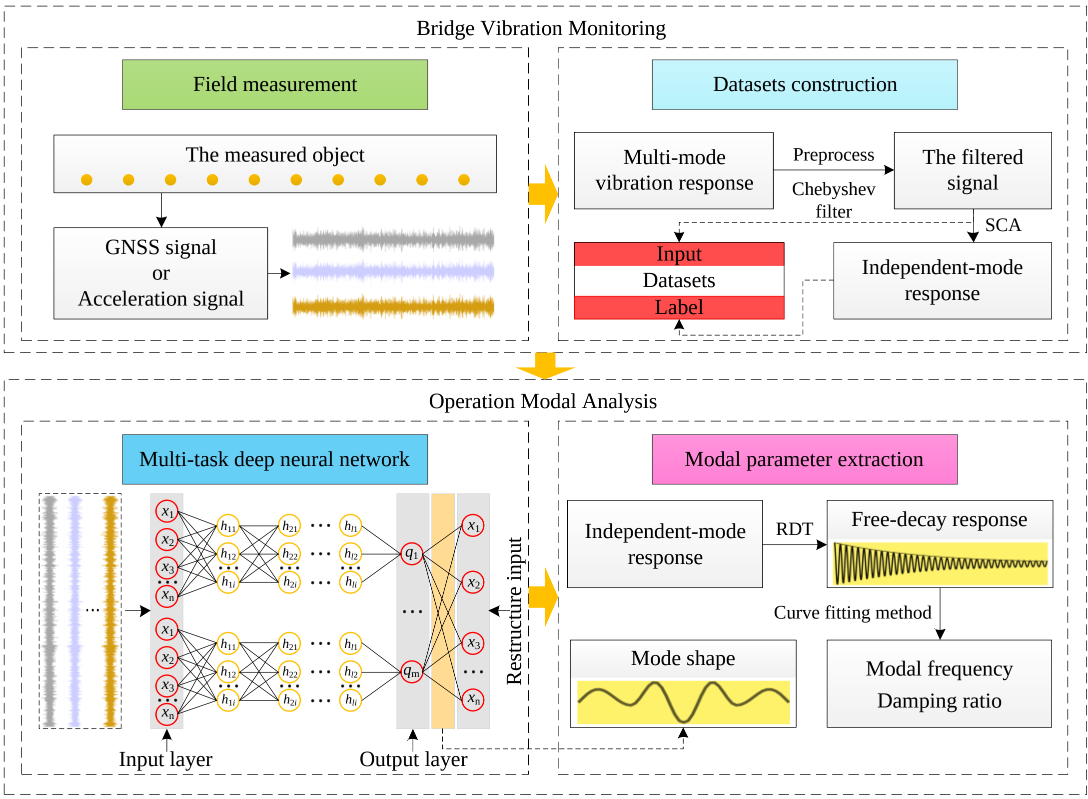

Figure 1. Proposed automatic modal identification approach.

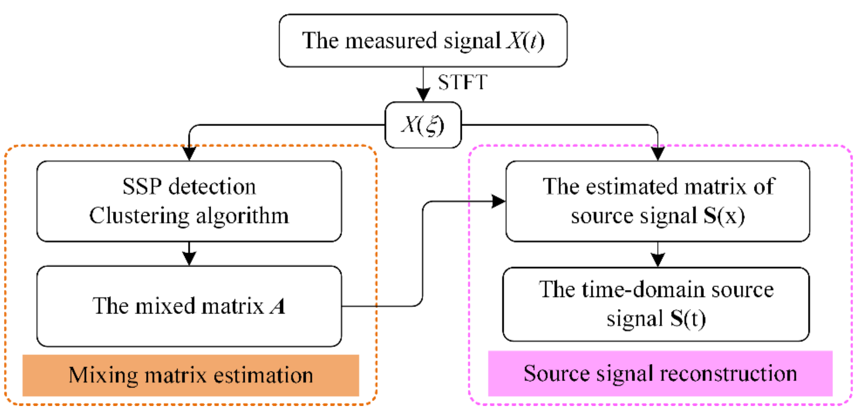

Figure 2. Principle of sparse component analysis approach

Multi-task Deep Neural Network

The designed MTDNN aims to separate source signals into independent modal responses automatically, thus enabling structural modal identification by RDT and curve fitting technique. Denote $\boldsymbol{X}$ as the origin vibration responses of structures collected by sensors. If there are n sensors, then $\boldsymbol{X}$ will have n channels as Eq. (1),

$$\mathbf{X}=\begin{pmatrix} x_{11} & \cdots & x_{1j} & \cdots & x_{1n} \\ \vdots & & \vdots & & \vdots \\ x_{i1} & \cdots & x_{ij} & \cdots & x_{in} \\ \vdots & & \vdots & & \vdots \\ x_{N1} & \cdots & x_{Nj} & \cdots & x_{Nn} \end{pmatrix}, \quad \mathbf{X}\in\mathbb{R}^{N\times n} \tag{1}$$

Where N denotes the number of sample points.

As shown in Figure 3, supposing that the source signal is comprised of m independent responses, then there will be m subnets, and each of them try to learn one independent response. The input of each subnet is source signal $\boldsymbol{X}$, therefore, the number of input neurons is kept consistent to the number of sensor channels. The number of hidden layers and number of neurons in the middle layer of the MTDNN, known as hyper-parameters, are determined by the training effect. It should be noted that the outputs from all subnets, donated as $\mathbf{Q}$ in Eq. (2), exactly represent modal responses,

$$\mathbf{Q}=(q_1,q_2,\cdots q_m)=\begin{pmatrix} q_{11} & \cdots & q_{1j} & \cdots & q_{1m} \\ \vdots & & \vdots & & \vdots \\ q_{i1} & \cdots & q_{ij} & \cdots & q_{im} \\ \vdots & & \vdots & & \vdots \\ q_{N1} & \cdots & q_{Nj} & \cdots & q_{Nm} \end{pmatrix}, \quad \mathbf{Q}\in\mathbb{R}^{N\times m} \tag{2}$$

Where each column represents one modal response. Meanwhile, the last output layer was the source signal. Therefore, the weight matrix, denoted as $\mathbf{W}$ in Eq. (3), between the penultimate and final layer will become the mode shapes of the structure

$$\mathbf{\Phi}=\mathbf{W}=\begin{pmatrix} w_{11} & \cdots & w_{1j} & \cdots & w_{1n} \\ \vdots & & \vdots & & \vdots \\ w_{i1} & \cdots & w_{ij} & \cdots & w_{in} \\ \vdots & & \vdots & & \vdots \\ w_{m1} & \cdots & w_{mj} & \cdots & w_{mn} \end{pmatrix}, \quad \mathbf{W}\in\mathbb{R}^{m\times n} \tag{3}$$

where each row corresponds to a mode shape.

The designed loss function, denoted as L in Eq. (4), contains two items, one is modal response loss L_1, and the other is reconstruction loss L_2.

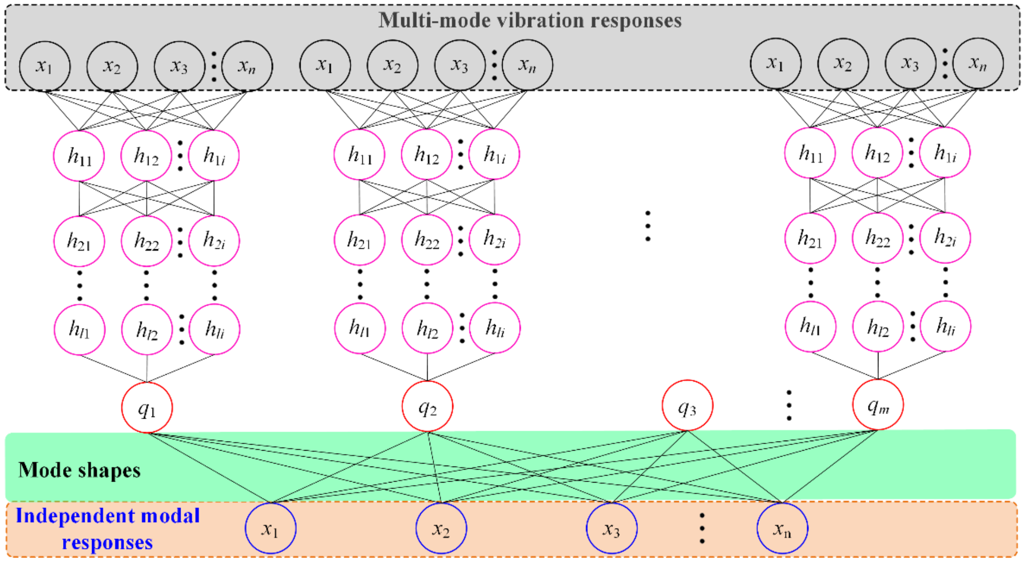

Figure 3. MTDNN architecture

$$L=\underbrace{\frac{1}{N}\sum_{l=1}^{m}\sum_{i=1}^{N}\left(q_{il}-\hat{q}_{il}\right)^2}_{L_1}+\underbrace{\frac{1}{N}\sum_{j=1}^{n}\sum_{i=1}^{N}\left(x_{ij}-\hat{x}_{ij}\right)^2}_{L_2} \tag{4}$$

Where x_{ij} and q_{il} denote source and independent modal responses, respectively; $\hat{x}_{ij}$ and $\hat{q}_{il}$ represent reconstructed and modal responses predicted by MTDNN. The Adam algorithm was adopted to train the developed MTDNN. Each subset was pre-trained first, and then the whole neural network was fine-tuned in a multi-task learning manner.

Free-decay Signal Acquisition using RDT

Based on the independent modal responses obtained from MTDNN, the RDT approach is implemented to extract the free-decay responses of structures. Then, modal frequencies and damping ratios of structures can be determined through the FFT and curve fitting approach. The corresponding mode shapes can be obtained by the weights between the penultimate layer and the last layer of the trained MTDNN.

EXPERIMENTAL VERIFICATION

The collected acceleration data from Tianjin Yonghe, located in Tianjin, China, was used to validate the proposed approach. It is a pre-stressed concrete cable-stayed bridge with three spans. As shown in Figure 4, five accelerometers (C1–C5) were attached to the bridge at 1/4, 1/2, and 3/4 of the main span, and 1/2 of the side spans, respectively, to monitor vibration responses of the bridge. The sampling rate is 100 Hz, and the experiment was performed for 9 hours from 9:00 a.m. to 6:00 p.m. on July 12, 2019.

When preparing data sets to train MTDNN, the cross-correlation function (CF) screening mechanism was adopted to eliminate spurious modal responses. Figure 5 demonstrates the decomposed signals from acceleration data. it can be seen that there are 12 independent modes including 7 spurious modes whose CF peak value was less than 0.5. Therefore, only physical modes were retained and used for data sets construction. In this study, 10000 s of the acceleration data collected after 3:00 pm were used. These signals were divided into training, validation, and test sets according to the ratio of 8:1:1.

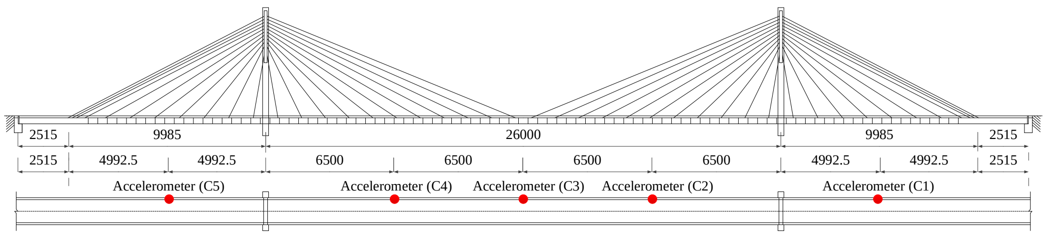

Figure 4. Locations of acceleration sensors on the bridge

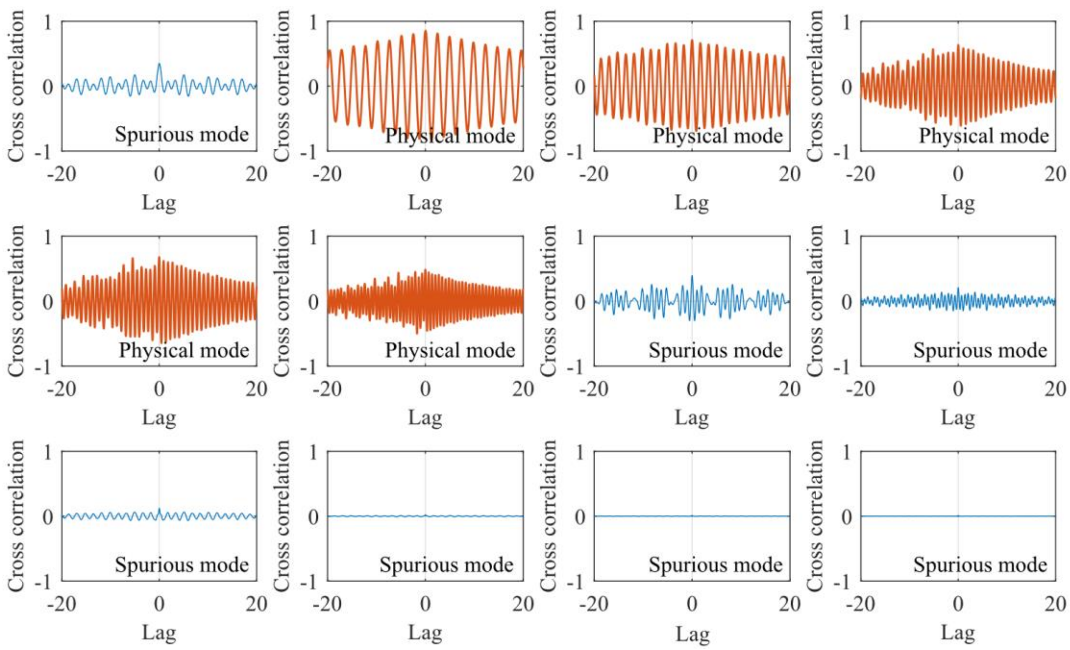

Figure 5. Determination of physical mode via CF screening mechanism based on acceleration

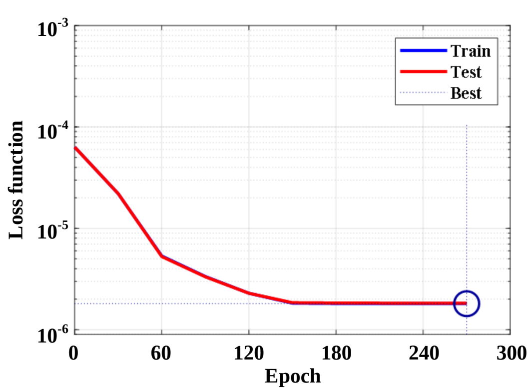

Figure 6. Loss-function drop curves of the MTDNN

TABLE 1. ESTIMATED MODAL PARAMETERS FROM ACCELERATION DATA.

Mode	Frequency (Hz)			Damping ratio (%)		
	SSI	FDD	MTDNN	SSI	FDD	MTDNN
1	0.4109	0.4124	0.4102	1.46	1.39	1.44
2	0.5886	0.5890	0.5886	1.26	1.28	1.20
3	0.9696	0.9703	0.9688	1.00	1.05	0.91
4	1.0952	1.0953	1.0950	0.89	0.87	0.87
5	1.4503	1.4503	1.4501	0..84	0.83	0.80

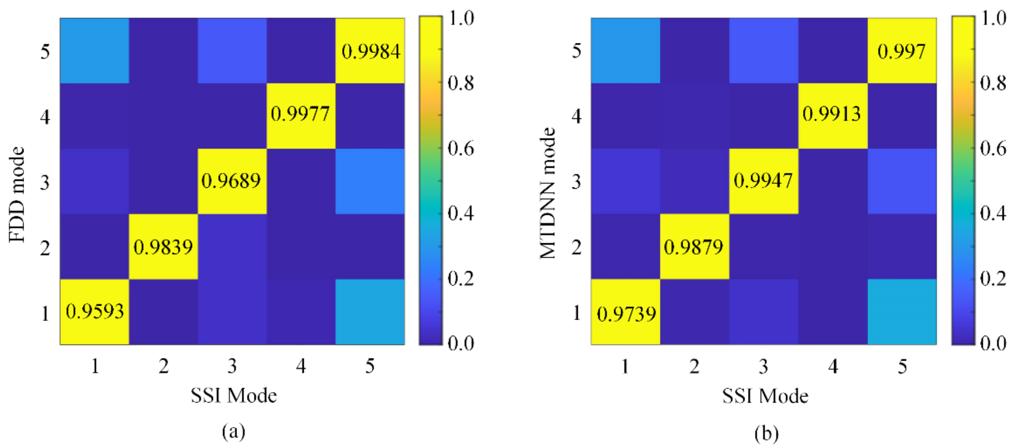

Figure 7. MAC values using different approaches: (a) FDD; and (b) MTDNN.

The designed MTDNN has 5 neutrons in the input layer corresponding to 5 acceleration channels C1-C5. The hidden layer contains 5 fully connected layers, each of which has 20 neurons. The penultimate layer contains 5 neurons corresponding to 5 physical modes, and the last layer also comprises 5 neurons corresponding to 5 channels of the source signal. The learning rate was set to 0.001 when training the designed MTDNN. The loss converges at epoch 250 as shown in Figure 6, indicating that MTDNN has learned the mapping relationship from source responses to independent modal responses

Once obtain the trained MTDNN, the test data was fed into it successively to get independent responses. RDT and curve fitting approach were also employed followingly to calculate frequencies and damping ratios. The results are listed in Table 1 including results obtained by SSI and FDD approaches. If treating SSI results as the reference, the identification errors of modal frequencies obtained by MTDNN and FDD are less than 0.17% and 0.36%, respectively. Meanwhile, Figure 7 also gives the results of mode shapes obtained from weights between the penultimate and final layer of MTDNN. It can be concluded that MTDNN also gives acceptable accuracy compared to SSI and FDD. It should be noted that MTDNN works in the prediction stage, and thus doesn't require any user intervention. Therefore, MTDNN provides an alternative approach for automated modal identification.

CONCLUSIONS

In this study, a multi-task deep neural network (MTDNN) is proposed to automate structural modal identification. An experiment on a long-span cable-stayed bridge showed that MTDNN gives precise modal results compared to the SSI approach. Based on this study, the following main conclusions were summarized:

- The proposed approach did not require any user intervention for the modal identification process. Once the MTDNN network training is completed, the new structural response data were input to the network to autonomously output independent modal responses. With the help of RDT and curve fitting approach, modal frequencies and damping ratios can be determined rapidly.
- The analysis results from the long-span cable-stayed bridge demonstrate that the developed MTDNN can automatically determine the modal parameters of structures with reliable accuracy. The MAC values derived by MTDNN and SSI are close to 1, also validating the significant identification accuracy of the proposed method.
- The proposed MTDNN provides an alternative approach for automated modal identification. Meanwhile, it also has the potential for real-time monitoring due to its rapid prediction speed.

REFERENCES

[1] J. Shu, C. Zhang, X. Chen, Y. Niu, Model-informed deep learning strategy with vision measurement for damage identification of truss structures, Mechanical Systems and Signal Processing. 196 (2023) 110327. https://doi.org/10.1016/j.ymssp.2023.110327.

[2] X. Zhang, W. Zhou, Y. Huang, H. Li, Automatic identification of structural modal parameters based on density peaks clustering algorithm, Structural Control and Health Monitoring. 29 (2022) e3138. https://doi.org/10.1002/stc.3138.

[3] M. Sun, M. Makki Alamdari, H. Kalhori, Automated Operational Modal Analysis of a Cable-Stayed Bridge, Journal of Bridge Engineering. 22 (2017) 05017012. https://doi.org/10.1061/(asce)be.1943-5592.0001141.

[4] D. Liu, Z. Tang, Y. Bao, H. Li, Machine-learning-based methods for output-only structural modal identification, Structural Control and Health Monitoring. 28 (2021) e2843. https://doi.org/10.1002/stc.2843.

[5] F. Amini, Y. Hedayati, Underdetermined blind modal identification of structures by earthquake and ambient vibration measurements via sparse component analysis, Journal of Sound and Vibration. 366 (2016) 117–132. https://doi.org/10.1016/j.jsv.2015.10.028.

[6] L. Zhen, D. Peng, Z. Yi, Y. Xiang, P. Chen, Underdetermined Blind Source Separation Using Sparse Coding, IEEE Transactions on Neural Networks and Learning Systems. 28 (2017) 3102–3108. https://doi.org/10.1109/TNNLS.2016.2610960.