Chapter 34
Bridge Structural Identification Using Moving Vehicle Acceleration Measurements

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Abstract Identification of dynamic characteristics of structures is a desired objective for existing infrastructure and has been accounted as a serious challenge for civil engineers. In this research, a structural identification method is proposed, which is capable of identifying dynamics of structures using sensor data inside vehicles passing over a bridge. The methodology utilizes a special type of identification algorithm facilitated by Expectation Maximization (STRIDEX) that is capable of identifying systems using mobile data networks. In this study, it is assumed that the mobile sensor measurements are the accelerations inside rigid vehicles and are primarily a mixtures of accelerations caused by the road roughness and bridge dynamic acceleration. With this regard, a stochastic State-Space model represents the equation of motion for a linear dynamic vehicle-bridge system consisting of an impure input. The observation vector is treated as a linear mixture of two sources that are not known. Therefore, the problem turns to a Blind Source Separation (BSS) procedure that is aiming to draw out the bridge vibrations from the mixture. An algorithm called Second Order Blind Identification (SOBI) has been utilized for source separation and validated using simulation. The entire algorithm, including both SOBI and STRIDEX acting together, could successfully identify natural frequencies and mode shapes of a numerical bridge model.

Keywords Expectation Maximization · Blind Source Separation · System Identification · Output Only Algorithms · Structural Health Monitoring

34.1 Introduction

System identification is a process that extracts mechanical properties of a dynamic system from different types of easy-to-access and cheap data channels such as accelerometer sensors. In recent years, many structural health monitoring (SHM) algorithms have been customized to utilization of wireless sensors, which form a flexible and efficient type of sensors in practice [1–5]. Wireless sensors are able to collect dense data and enjoying an increasingly more powerful on-board microprocessor, they are able to communicate with the control nodes more efficiently [6, 7].

System identification procedure is usually laid on a mathematical framework [8]. The governing equation of motion for dynamic systems is a second order differential equation in which the system's degrees of freedom are included as independent variables as shown in Eq. 34.1:

$$M\ddot{U}[n] + C\dot{U}[n] + KU[n] = F \tag{34.1}$$

Because of the inherent complexity of the conventional form of the equation of motion, in system identification application State Space modal is utilized as in [9]:

$$x_k = Ax_{k-1} + n_k \tag{34.2}$$

$$y_k = Cx_k + v_k \tag{34.3}$$

$$x_1 \sim N\left(\bar{\mu}, \bar{V}\right) \tag{34.4}$$

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$$\eta_k \sim N(0, Q) \tag{34.5}$$

$$\nu_k \sim N(0, R) \tag{34.6}$$

where A is the state matrix, C is the observation matrix, x_k is the state vector which is not observable, and y_k is the observation vector which is the collected data at the accessible channels. η_k and ν_k are systemic and sensing noises respectively, which for simplicity are assumed to be uncorrelated Gaussian white noise with covariance matrices as Q and R [10].

In the case of structural engineering application, it is often not possible to accurately measure the input of the dynamic system, e.g. loads. For example, in case of bridge system identification, an accurate description of traffic load or wind load is extremely challenging. As a result, identification problems of output-only systems have been studied extensively [11, 12].

In general, there are numerous types of system identification methods, which are proper for different applications. In SHM, two general approaches are common: frequency domain and time domain identifications. Time domain identification algorithms such as Eigensystem Realization Analysis (ERA) [13], ERA using exogenous excitations (ERA-NExT), ERA using Observer Kalman Filter Identification (ERA-OKID) [12] and SubSpace Identification (SSI) [14] are a few examples of algorithms for real-time monitoring and asymptotically converge to the more accurate results as the time passes. In this study, STRIDEX [15], a more recent algorithm which is not only capable of time-domain identification, but also is appropriate for mobile sensing networks is utilized.

Structural Identification using Expectation Maximization (STRIDE) [16] is a novel state space-based procedure that uses Expectation Maximization (EM) algorithm [17] to iteratively maximize the estimation of the unobserved state vector and unknown state-space matrices and is developed for output-only identification. The algorithm defines a super parameter, which consists of all state space unknowns as shown in Eq. 34.7 and then assuming a given set of unobserved states, maximizes the log-likelihood function of the state space model (Maximization Step).

$$\Psi = \left(\bar{\mu}, \bar{V}, A, Q, C, R\right) \tag{34.7}$$

$$\begin{aligned}\log L\left(\Psi | x, y\right) = &-\frac{pN}{2}\ln(2\pi) - \ln\left|\bar{V}\right| - \frac{1}{2}(x_1-\bar{\mu})^T\bar{V}^{-1}(x_1-\bar{\mu}) - \frac{KN}{2}\ln(2\pi) - \frac{K}{2}\ln|R| \\ &- \frac{1}{2}\sum_{k=1}^{K}(y_k - Cx_k)^T R^{-1}(y_k - Cx_k) - \frac{(K-1)\,pN}{2}\ln(2\pi) - \frac{K-1}{2}\ln|Q| \\ &- \frac{1}{2}\sum_{k=2}^{K}(x_k - Ax_{k-1})^T Q^{-1}(x_k - Ax_{k-1}).\end{aligned} \tag{34.8}$$

In order to estimate unobserved states, in the Expectation Step of the algorithm, STRIDE implements Kalman Filter and Rauch-Tung-Striebel (RTS) smoother on the input data. STRIDE is an asymptotically converging algorithm that finds a local maximum. However, to capture the highest local maximum (global maximum), initialization of the super parameter is crucial. The algorithm has shown to be computationally rapid and inexpensive in [16].

A distinctive feature of STRIDE is its ability to upgrade for mobile sensing networks. STRIDEX is different formulation of STRIDE in which the position of mobile sensors are assumed known at each time step. Consequently, the new state-space equations for the mobile sensing problem are:

$$x_k = Ax_{k-1} + n_k \tag{34.9}$$

$$y_k = \Omega_k C x_k + v_k \tag{34.10}$$

As indicated in the governing equations, despite the time varying observation matrix $\Omega_k C$, this set of equations can still be solved with EM, knowing that mode shape regression matrix Ω_k is given for each time step. The mode shape regression matrix (MSR) is a transformation matrix that converts moving measurements at an arbitrary set of sensing nodes to the measurements of prefixed Virtual Probing Locations (VPL) that are stationary.

Fig. 34.1 Schematic idea of the mobile sensing

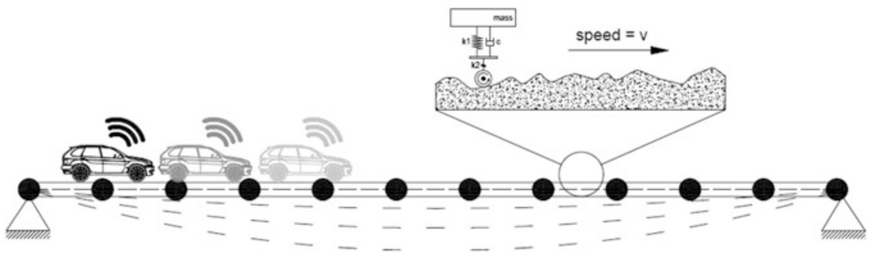

Fig. 34.2 Generic figure of the numerical model

One of the most significant challenges for utilizing STRIDEX for mobile sensing is the intense contamination of the structural vibration caused by physical distractions. Specifically, for bridge health monitoring application, sensing vehicles are passing over a pavement with a certain roughness (Figs. 34.1 and 34.2), whose spatial profile produces oscillating patterns that affect the bridge vibration measurements [3]. In other words, the acceleration time history that is recorded by the moving sensors is not collecting only the bridge dynamic response, but also the vibrations induced by the surface roughness. Therefore, in order to feed the identification algorithm by a valid input, a blind source separation (BSS) of mixed data should be used. In the literature, many algorithms have been proposed for separating mixed signals to their initial sources, each of which has some limitations. Among these, Independent Component Analysis (ICA) [18, 19] and Second Order Blind Identification (SOBI) [20, 21] has been practiced more often and performed better for civil engineering applications.

In the BSS literature, ICA is one of the commonly used and thoroughly evaluated algorithms [18]. In ICA, the principal assumption is that the sources are statistically independent and at least one of them is non-Gaussian. These two assumptions lead the algorithm to find the independent components of a mixed signal. Note that the independent sources may not be the sources that are actually mixed, but the most independent sources that can be pulled out of the mixtures, regardless of their physical interpretation. Moreover, the algorithm guarantees the most statistically possible independent sources, which is much stronger than uncorrelatedness. The algorithm tries to maximize non-Gaussianity by maximizing corresponding quantitative metrics, such as the forth order cumulant or Kurtosis.

Despite ICA's great ability to separate mixed data into its original sources, it is implicitly clear that it does not consider the sequence of samples by parameters such as autocorrelations or spectral densities [21]. In fact, it treats a signal as data points without orders in a way that the sequence is not of a great importance. However, in case of mixed signals, especially when they are contaminated versions of structural dynamic responses, samples order is indeed significant, since their temporal correlation make up the response spectrum from which the identification can be performed. To address this drawback, SOBI algorithm is utilized, which is a more robust alternative that benefits, whenever possible, of the temporal structure of the sources for facilitating their separation [20]. SOBI is more suitable for mixed signals with sources of different spectral contents, which is often the case in structural dynamics [21]. In this algorithm a weaker version of independency, which is covariance - a second order statistical moment - is of interest. As a result, SOBI is not only more desirable because of its ability of capturing temporal sequences for structural dynamics vibrations, but also is a computationally less expensive algorithm than ICA, since it does not consider higher than the second order independencies.

In this study, a numerical model of a bridge is made in OpenSees and the mobile sensor records are simulated. Primarily, these measures are not manipulated by the road profile roughness, so a sample generator MATLAB code has been developed to produce mixed signals. In the second phase, the polluted mixtures are fed through the SOBI algorithm to find both roughness-caused and the dynamic response vibrations of the bridge. Finally, a group of separated dynamic responses is input to the STRIDEX to identify natural frequencies and the mode shapes. Detailed explanation of each part will be given in the following sections. A flow chart of the proposed structural system identification algorithm is demonstrated below (Fig. 34.3).

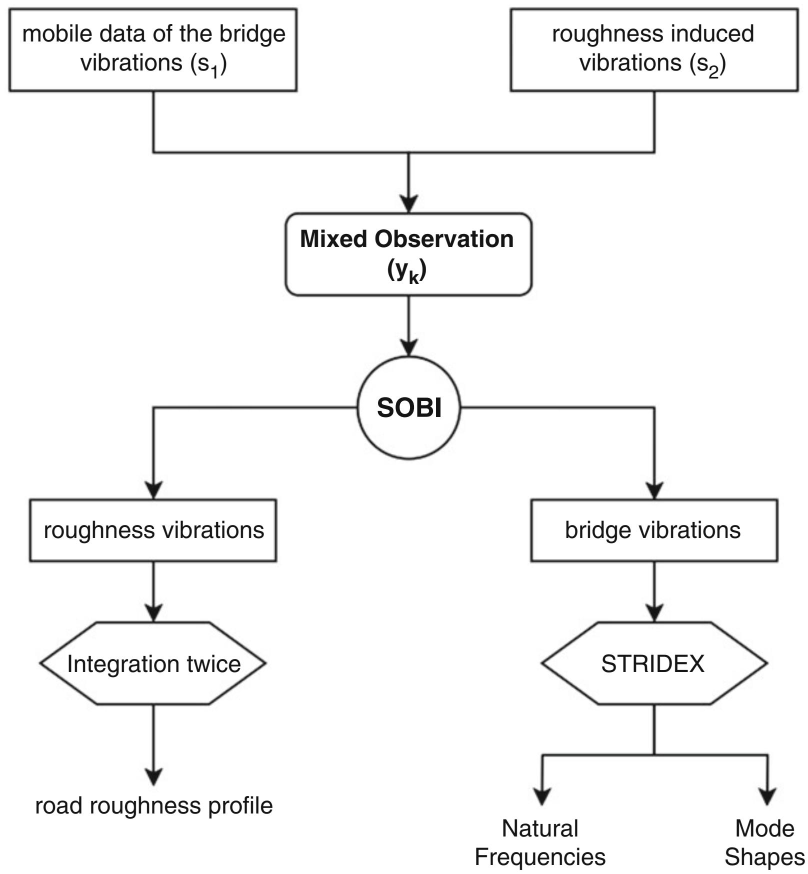

Fig. 34.3 Flow-chart of the proposed identification algorithm

34.2 Problem Statement

A 2D model of a 120 m long simply supported, single span bridge is built in OpenSees. The span is divided be 4800 pieces to make a 4801 degrees of freedom system and lateral accelerations are recorded at all DOFs for 114 sec. A set of nine wind load time histories is generated using spectral representation method [22] and applied on nine DOFs evenly spaced along the span. The wind intensity is mild and is supposed to act like an ambient random loading on the structural system.

After collecting data of the dense matrix function of accelerations at each DOFs per time, mobile sensor vectors has to be produced. Regarding that, based on the sensing vehicle speed and at each time step, one sample is chosen from a column that is attributed to the location of vehicle at that specific time [23]. The mobile sensing vector generation has been illustrated in the figure below (Fig. 34.4).

After composing mobile sensing data, it is needed to linearly add roughness-induced vibrations to these data to generate mixed signal samples. The road roughness profile is commonly assumed to be a zero mean stationary Gaussian random process [24]. In the present study, the following power spectral density (PSD) function for the roughness profile is utilized [25, 26]:

$$\varphi(n) = \varphi\left(n_0\right)\left(\frac{n}{n_0}\right)^{-2}; \quad \left(n_1 < n < n_2\right) \tag{34.11}$$

where n = spatial frequency (cycle/m); n_0 = discontinuity frequency of 1/2π (cycle/m); $\varphi(n_0)$ = road roughness coefficient (RRC) (m^3/cycle) dependent to the road condition (ISO 1995 gives five categories of very good, good, fair, poor, and very poor). Here, a good road condition with $\varphi(n_0) = 120e{-6}$ is selected and the road roughness profile is generated with spectral representation technique using Eq. 34.12:

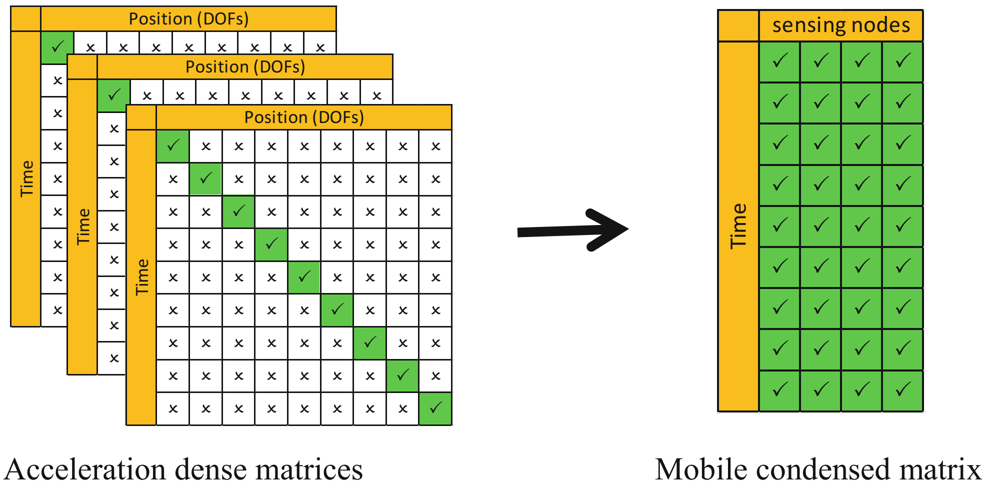

Fig. 34.4 Mobile sensing data generation using acceleration dense matrix

$$r(x) = \sum_{k=1}^{N} \sqrt{2\varphi\left(n_k\right)\Delta n}\cos\left(2\pi n_k x + \theta_k\right) \tag{34.12}$$

where N = spatial frequency depending on the length of the road, θ_k = random phase angle uniformly distributed from 0 to 2π; φ = PSD function for the road surface; n_k = wave number (cycle/m). Note that the generated random function is not a function of time, and as a result, cannot be directly added to the mobile sensor records. Moreover, since the mobile sensors collect accelerations, the roughness displacement profile has to be differentiated twice to give accelerations caused by the roughness. The spatial profile can be transformed to a time series signal with respect to the moving sensor's speed. In this numerical analysis, the sensor's velocity is tuned in a way that for each time step, sensor proceeds one DOF further and collect data on that point. That implies the mobile sensing vector can be acquired by diagonalization of the submatrix of the dense matrix.

At this point, since the generation of the mixed signal samples is completed, the goal is to identify the bridge structural system using these mixed signals that are intensively disturbed by the roughness-induced vibrations. In this study, the approach to solve this problem is to use SOBI method as a successful blind source separation algorithm for distinctive spectral sources. In the next section, SOBI is explained and implemented on the mixed data to draw out bridge dynamic vibrations from the mixed signals using which STRIDEX can identify the modal properties.

34.3 Second Order Blind Identification (SOBI)

In general, a mixed signal is not necessarily a weighted sum of several sources and may be a convolution or nonlinear mixture of the sources. However, in the present application, it is assumed that the mobile sensors seat on rigid vehicles that do not convolve linear mixture of roughness-caused and bridge dynamics vibrations. Therefore, the noisy mixed signals can be expressed as:

$$x_i(t) = \sum_{j=1}^{n} a_{ij} s_j(t) + \sigma_i(t), \qquad i = 1, 2, \ldots, n \tag{34.13}$$

and in the matrix notation:

$$\boldsymbol{x}(t) = \boldsymbol{A}\boldsymbol{s}(t) + \boldsymbol{\sigma}(t) = \boldsymbol{y}(t) + \boldsymbol{\sigma}(t) \tag{34.14}$$

where $\boldsymbol{A}$ is the mixing matrix and $\boldsymbol{\sigma}(t)$ is an uncorrelated noise vector. $\boldsymbol{s}(t)$ is also a vector of sources at time t and apparently, $\boldsymbol{x}(t)$ is the mixed observation. It is assumed that the mixture matrix is an unknown constant matrix that is to be estimated based on the observations. Note that it is a common assumption that the sources are unit variance random processes, so $E\left[s_i^2(t)\right] = 1$for $i = 1, 2, \ \ldots, n$.

As a result, if sources are stationary, uncorrelated and unit variance, the covariance matrix is:

$$\boldsymbol{R}_s(0) = E\left[\boldsymbol{s}(t)\boldsymbol{s}^*(t)\right] = \boldsymbol{I} \tag{34.15}$$

where $\boldsymbol{s}^*(t)$ is the conjugate transpose of vector $\boldsymbol{s}(t)$. Using Eq. 34.14 and supposing the additive noise vector is uncorrelated and independent to the sources, it implies:

$$\boldsymbol{R}_x(0) = E\left[\boldsymbol{x}(t)\boldsymbol{x}^*(t)\right] = E\left[\boldsymbol{A}\boldsymbol{s}(t)\boldsymbol{s}^*(t)\boldsymbol{A}^H\right] + E\left[\boldsymbol{\sigma}(\boldsymbol{t})\,\boldsymbol{\sigma}^*(\boldsymbol{t})\right] = \boldsymbol{A}\boldsymbol{A}^H + \sigma^2\boldsymbol{I} \tag{34.16}$$

SOBI can be implemented in two steps, which the first is whitening. A linear transformation **W** can be easily calculated such that: $E[\boldsymbol{W}\boldsymbol{y}(t)\boldsymbol{y}^*(t)\boldsymbol{W}^H] = \boldsymbol{I}$. On the other hand, from covariance matrix of the noisy observation, it is obvious that: $E[\boldsymbol{y}\boldsymbol{y}^*] = \boldsymbol{A}\boldsymbol{A}^H$, hence:

$$E\left[\boldsymbol{W}\boldsymbol{y}\boldsymbol{y}^*\boldsymbol{W}^H\right] = \boldsymbol{W}\boldsymbol{A}\boldsymbol{A}^H\boldsymbol{W}^H = \boldsymbol{I} = \boldsymbol{U}\boldsymbol{U}^H \tag{34.17}$$

So, using the whitening matrix $\boldsymbol{W}$, a unitary matrix $\boldsymbol{U}$ can be found such that: $\boldsymbol{U} = \boldsymbol{W}\boldsymbol{A}$. Note that the actual observation is not $\boldsymbol{y}$, but $\boldsymbol{x}$, which has noise effects, thus if say $z(t) = \boldsymbol{W}\boldsymbol{x}(t)$:

$$E\left[zz^*\right] = \boldsymbol{E}\left[\boldsymbol{W}\boldsymbol{x}\boldsymbol{x}^*\boldsymbol{W}^H\right] = \boldsymbol{W}\boldsymbol{R}_{\boldsymbol{x}}(0)\boldsymbol{W}^H \tag{34.18}$$

The second step is to determine the unitary matrix U, considering time lagged observation covariance matrix, as shown below:

$$\boldsymbol{R}_z^w(\tau) = E\left[z(t+\tau)\,z^*(t)\right] = \boldsymbol{W}\boldsymbol{E}\left[\boldsymbol{x}(t+\tau)\,\boldsymbol{x}^*(t)\right]\boldsymbol{W}^H = \boldsymbol{W}\boldsymbol{A}E\left[\boldsymbol{s}(t+\tau)\,\boldsymbol{s}^*(t)\right]\boldsymbol{A}^H\boldsymbol{W}^H, \quad \forall\tau \neq 0 \tag{34.19}$$

which gives $\boldsymbol{R}_z^w(\tau) = \boldsymbol{U}\boldsymbol{R}_{\boldsymbol{s}}(\tau)\,\boldsymbol{U}^H$. The key idea to find $\boldsymbol{U}$ is that since it is a unitary matrix, and it was previously assumed that the sources are uncorrelated, implying that $\boldsymbol{R}_{\boldsymbol{s}}(\tau)$ is diagonal, therefore it is realized that any whitened covariance matrix $\boldsymbol{R}_z^w(\tau)$ is diagonalizable by the unitary transform $\boldsymbol{U}$. To determine such a matrix, it is just required to decompose the time-lagged covariance matrix of the whitened observation $\boldsymbol{R}_z^w(\tau)$ and accordingly, $\boldsymbol{A}$ can be found from $\boldsymbol{U} = \boldsymbol{W}\boldsymbol{A}$ and finally, sources as $\boldsymbol{x}(t) = \boldsymbol{A}\boldsymbol{s}(t)$. The blind source separation using SOBI is completed here. The entire SOBI calculation is coded through a built-in MATLAB toolbox for SOBI [27] and the package has been used in the present study.

After the separation procedure on the mixed signals via SOBI, the separated source which is recognized as the bridge vibration is fed to the STRIDEX algorithm and the modal properties are extracted.

34.4 Numerical Modeling of a 4800-DOF Beam

To evaluate the proposed procedure for structural identification, the aforementioned simply supported beam is assessed as a simplified bridge model. In a mobile sensing procedure, the dynamic response of the bridge for six moving sensors according to a specific movement path as shown in Fig. 34.5 are simulated via the dense matrix. Note that for each sensor, the regional distance is scanned twice to collect more data. Sensor placement is a sensitive parameter that affects the identification quality. In this study, the same placement as used to validate STRIDEX in [15] has been considered. However, thorough discussions on sensor placement can also be found in [32, 32] for different types of structures. The experimental results of various sensor placements are also shown in [32] and effects are discussed.

The sensors' data are dynamic responses of the structure, which are not realistic measurements, since they are not affected by the roughness-induced vibrations. Therefore, a time signal of vertical accelerations caused by road roughness is generated via spectral representation technique and added up with the bridge acceleration in a synchronized fashion. Finally a Gaussian noise is added to consider measurement errors of the sensors. The PSDs for both pure and mixed signals are presented in Fig. 34.6. As illustrated, the frequency content of the bridge vibration is clearly indicator of the natural frequencies of the model via the location of the sharp spikes on the PSD. However, this clarity is not observable anymore on the mixed signal PSD. Correspondingly, structural identification using mixed signals does not seem a plausible desire, since the input is highly disturbed.

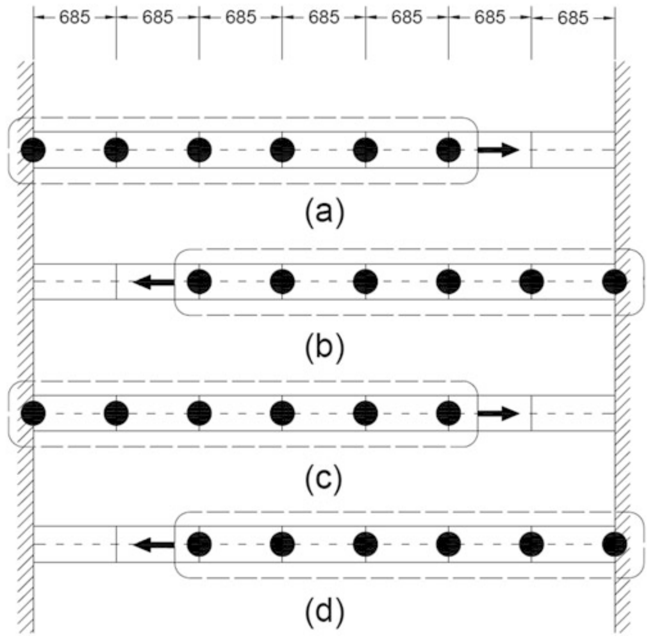

Fig. 34.5 Configuration of moving sensors. a-d showing scanned paths

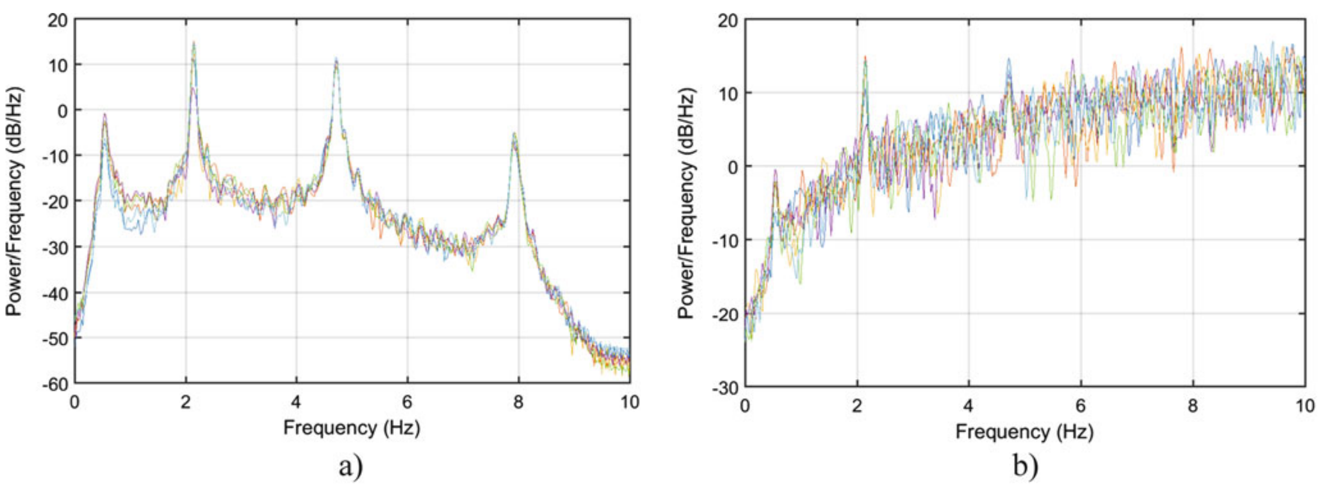

Fig. 34.6 Welch Power Density Spectra (**a**) Bridge vibration only signal (**b**) Mixed signal

After generating samples, the mixed signals are fed to the SOBI algorithm in order to draw out the source signals, which is expected to be bridge dynamic and roughness-caused vibrations. An example of a mixed signal and the corresponding separated sources from SOBI versus time is shown in Fig. 34.7. The spectra for the mixed and source signals are displayed in Fig. 34.8 as well. The first source spectrum, which is correlated to be the bridge vibration, is showing spikes in the same location as the bridge natural frequencies, although these spikes are not visible in the other source and also the mixed spectra. It should be noted that although the first source is not identical to the reference signal in time, it is a linearly transformed version which is practically of the same value, thanks to the SOBI formulations.

On the other hand, if compare the second detected source against the generated roughness-caused acceleration, a significant compliance can be realized, as indicated in Fig. 34.9. This can be promising for the road roughness identification using mobile sensors' records. In fact, since the SOBI is successful to extract roughness-induced part of a mixed signal, the operator can simply find the road roughness pattern by differentiating the mined signal twice and find the roughness profile.

The last phase is to use the implementation of the extracted sources that are correlated to the bridge dynamic responses, to the STRIDEX identification algorithm. For each mobile sensor, one source is mined out as the bridge vibration and fed to the STRIDEX. In this identification algorithm, the accelerations of the mobile sensors at each time steps and locations are

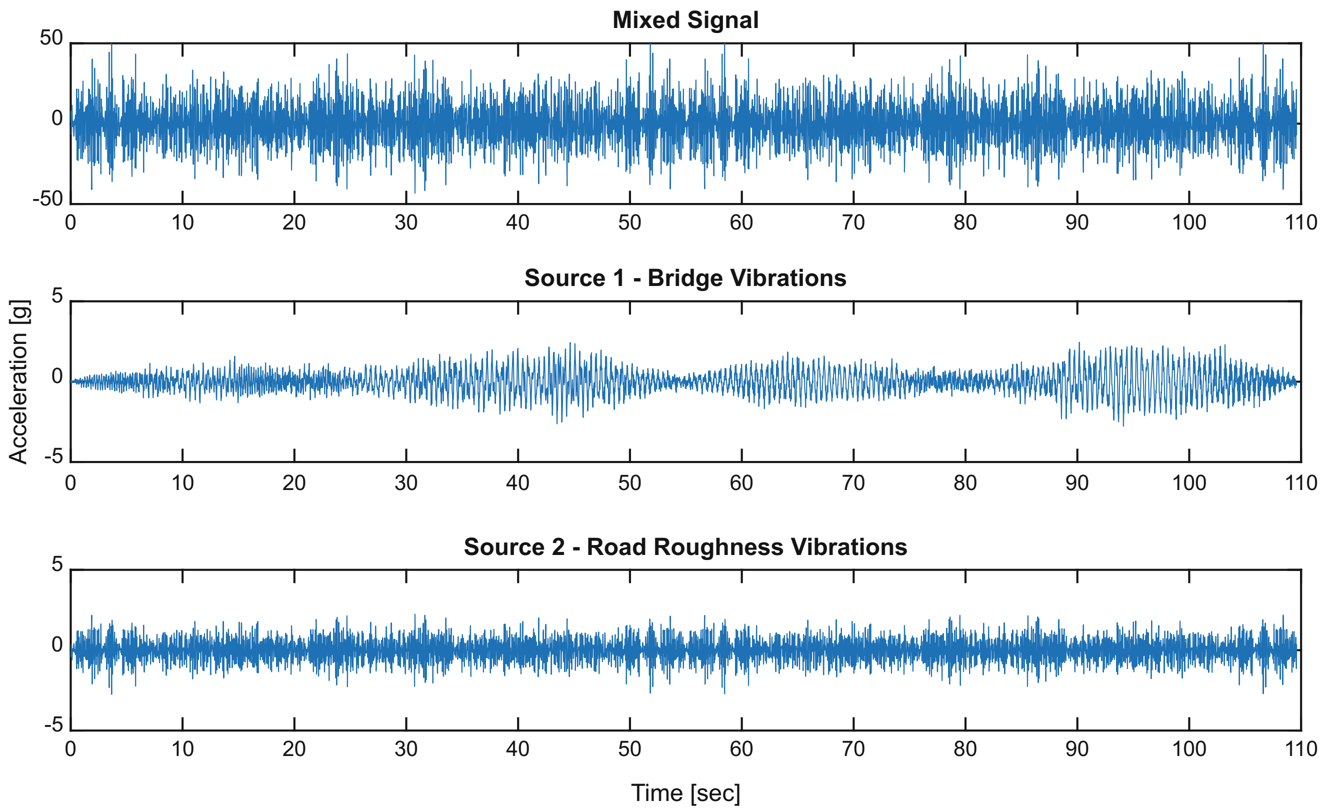

Fig. 34.7 SOBI performance on a mixed signal

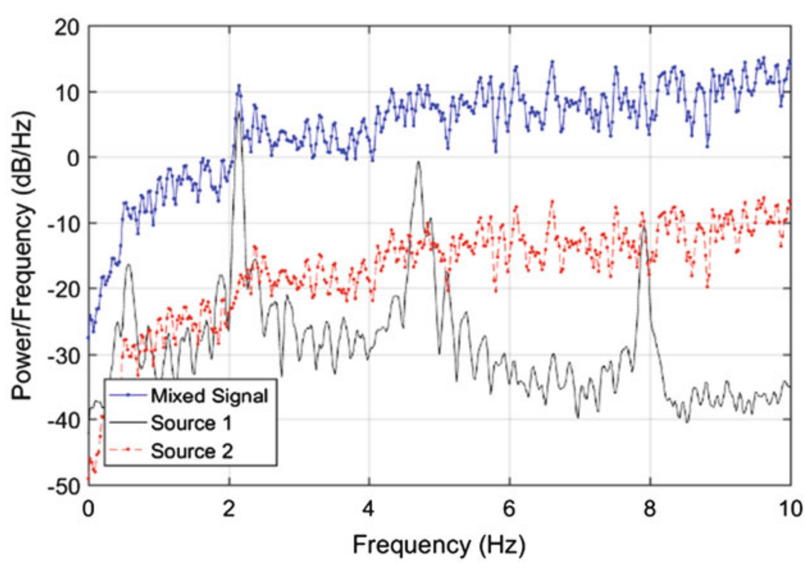

Fig. 34.8 Spectra for mixed and separated signals

mapped to the associated accelerations on preset virtual probing locations (VPL) that are stationary. Therefore, the method is able to enhance the identified modal properties by changing the VPLs, but feeding only one set of data. In this study, three VPLs are considered and their locations are shown in Table 34.1.

The identification algorithm is executed and the results are shown in Fig. 34.10 and Table 34.2. Note that the maximum likelihood-based identification methods can be concluded as a set of sensitivity metrics which are more informative than scalar results shown in this study [32]. However, for simplicity, in the presented evaluation, the representative scalar metrics

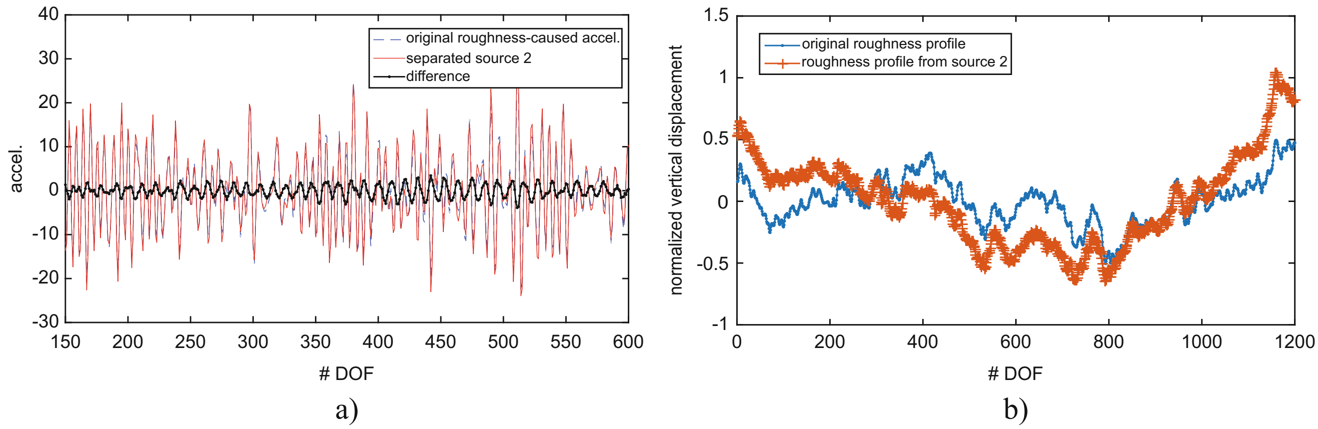

Fig. 34.9 Comparison between generated and separation-derived roughness (**a**) Acceleration difference (**b**) Profile difference

Table 34.1 Virtual probing locations

	DOF label					
VPL set	1	2	3	4	5	6
1	685	1370	2055	2740	3425	4110
2	342	1027	1712	2397	3082	3767
3	1027	1712	2397	3082	3767	4452

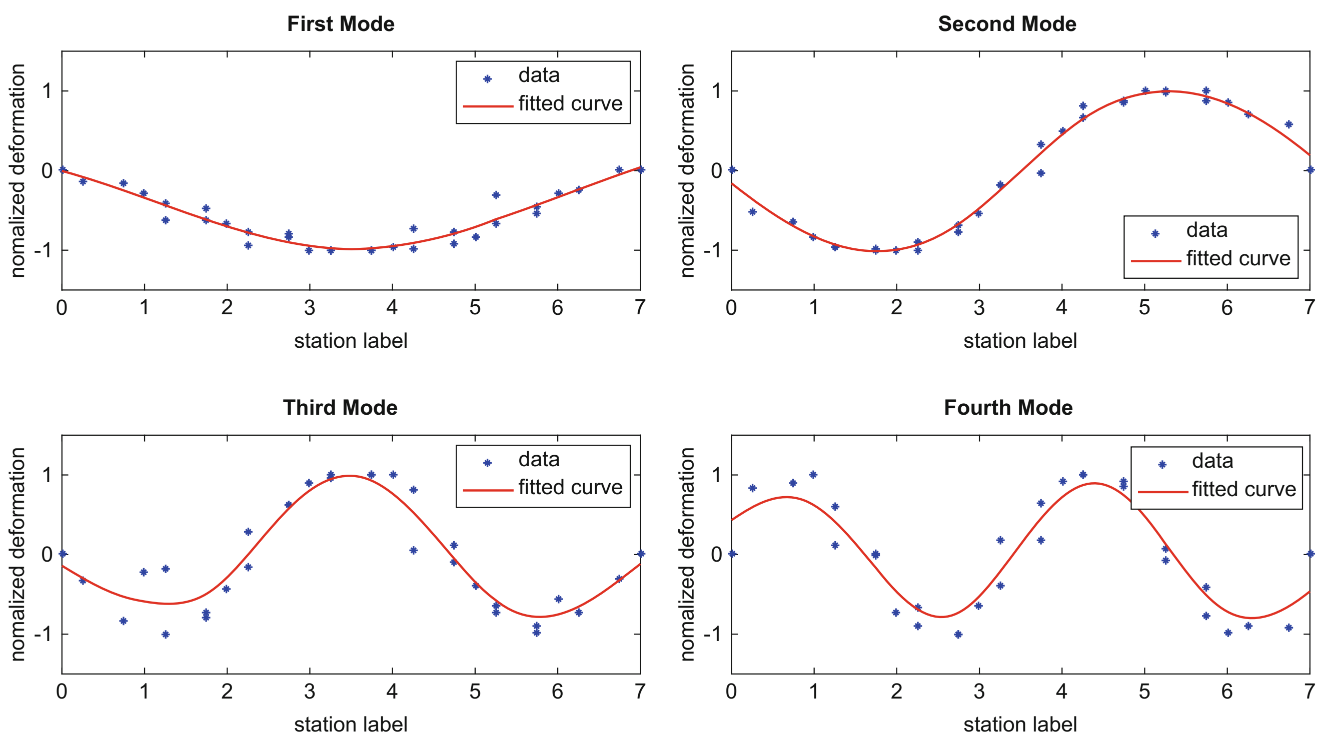

Fig. 34.10 Mode shapes derived by STRIDEX using separated signals

are assessed. As it is shown, the algorithm is able to identify fundamental modes clearly and estimate natural frequencies and mode shapes. In Fig. 34.10, for each mode shape, asterisk points are showing VPL locations for five different VPL sets and the curve is a spline that is best-fitted for these points. The algorithm is also fairly capable to estimate Rayleigh damping ratios, which were tuned in a way to show 1% modal damping on first and second modes. However, the algorithm is not very effective to identify the first mode and its corresponding attributes.

Table 34.2 Frequencies and damping ratios for first four modes

VPL set	Frequency (Hz) f1	f2	f3	f4	Damping ratio (%) ξ1	ξ2	ξ3	ξ4
1	0.638	2.162	4.711	7.933	NaN	0.720	0.870	5.270
2	0.615	2.168	4.711	7.750	NaN	2.300	1.950	9.580
3	0.744	2.164	4.722	7.911	NaN	1.450	2.210	8.360
Mean	0.666	2.165	4.715	7.865	NaN	1.490	1.677	7.737
Exact	0.541	2.165	4.871	8.660	1.000	1.000	Unknown	Unknown
Error (%)	22.99	−0.01	−3.21	−9.18				

34.5 Conclusion

In this study, a new approach for structural system identification using mobile sensing networks has been proposed. The idea is to separate mixed signals collected by mobile sensors to the producing sources, one of which is the bridge dynamic response. The separated signal may not be identical to the producing source signal, however it is closely related and inherit the same temporal characteristics.

The numerical modeling and validation have exhibited an acceptable performance for the proposed procedure. The Second Order Blind Identification (SOBI) was successful to separate linearly mixed signals. Moreover, the roughness part of the separated sources is also highly correlated to the original roughness profile. This observation offers that the proposed algorithm is capable to have two-folded applications on both bridge and pavement identification simultaneously, without any preliminary information needed.

34.6 Future Works

The proposed algorithm has shown promising results, however it is still needed to be more robust in order to accurately identify the first mode properties. In addition, in order to verify the eligibility of the proposed procedure, a verification on experimental or real data is highly required, which is in progress.

A fruitful extension of this work is to utilize a convolutional source separation algorithm instead of the SOBI, since it is more convenient to feed mobile sensors' data directly into the procedure.

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References

1. Pakzad, S.N., Fenves, G.L., Kim, S., Culler, D.E.: Design and implementation of scalable wireless sensor network for structural monitoring. J. Inf. Syst. **14**(1), 89–101 (2008)
2. Swartz, R.A., Lynch, J.P.: Strategic network utilization in a wireless structural control system for seismically excited structures. J. Struct. Eng. **135**(5), 597–608 (2009)
3. Kim, J., Lynch, J.P.: Experimental analysis of vehiclebridge interaction using a wireless monitoring system and a two-stage system identification technique. Mech. Syst. Signal Process. **28**, 3–19 (2012)
4. Cho, S., et al.: Structural health monitoring of a cable-stayed bridge using wireless smart sensor technology: data analyses. Smart Struct. Syst. **6**(5–6), 461–480 (2010)
5. Dorvash, S., Pakzad, S.N., Cheng, L.: An iterative modal identification algorithm for structural health monitoring using wireless sensor networks. Earthq. Spectra. **29**(2), 339–365 (2013)
6. Sohn, H., Farrar, C.R., Hemez, F.M., Czarnecki, J.J.: A Review of Structural Health Review of Structural Health Monitoring Literature 1996–2001. Los Alamos National Laboratory, Los Alamos, NM (2002)
7. Farrar, C.R.: Structural health monitoring: technological advances to practical implementations. Proc. IEEE. **104**(8), 1508–1512 (2016)
8. Juang, J.-N.: Applied System Identification, 1st edn. Prentice Hall, New York (1994)
9. Peeters, B., De Roeck, G.: One-year monitoring of the Z 24-bridge: environmental effects versus damage events. Earthq. Eng. Struct. Dyn. **30**(2), 149–171 (2001)

10. Matarazzo, T.J., Pakzad, S.N.: Direct state-space models for time-varying sensor networks. Proc. 10th Int. Structural Health Monitoring 2015. **7**, 59–65 (2015)
11. Chang, M., Asce, S.M., Pakzad, S.N., Asce, A.M.: Observer Kalman filter Identification for output-only systems using interactive structural modal identification toolsuite. J. Bridg. Eng. **19**, 1–11 (2014)
12. Chang, M., Pakzad, S.N.: Observer Kalman filter identification for output-only systems using interactive structural modal identification toolsuite. J. Bridg. Eng. **19**(5), 4014002 (2013)
13. Juang, J.-N., Pappa, R.S.: An eigensystem realization algorithm for modal parameter identification and model reduction. J. Guid. **8**(5), 620–627 (1985)
14. Van Overschee, P., De Moor, B.L.: Subspace Identification for Linear Systems: Theory—Implementation—Applications. Springer Science & Business Media, Berlin (2012)
15. Matarazzo, T.J., Pakzad, S.N.: Scalable structural modal identification using dynamic sensor network data with STRIDEX. Comput. Civ. Infrastruct. Eng. **33**(1), 4–20 (2018)
16. Matarazzo, T.J., Pakzad, S.N.: STRIDE for structural identification using expectation maximization: iterative output-only method for modal identification. J. Eng. Mech. **142**(4), (2016)
17. Shumway, R.H., Stoffer, D.S.: Time Series Analysis and Its Applications, vol. 97. Springer, Cham (2011)
18. Oja, E., Hyva, A.: Independent component analysis: algorithms and applications. Neural Netw. **13**, 411–430 (2000)
19. Kerschen, G.Ã., Poncelet, F., Golinval, J.: Physical interpretation of independent component analysis in structural dynamics. Mech. Syst. Signal Process. **21**, 1561–1575 (2007)
20. Belouchrani, A., Abed-Meraim, K., Cardoso, J.-F., Moulines, E.: A blind source separation technique using second-order statistics. IEEE Trans. Signal Process. **45**(2), 434–444 (1997)
21. Poncelet, F., Kerschen, G., Golinval, J., Verhelst, D.: Output-only modal analysis using blind source separation techniques. Mech. Syst. Signal Process. **21**, 2335–2358 (2007)
22. Shinozuka, M., Deodatis, G.: Simulation of stochastic processes by spectral representation. Appl. Mech. Rev. **44**(4), 191–204 (1991)
23. Matarazzo, T.J., Pakzad, S.N.: Truncated physical model for dynamic sensor networks with applications in high-resolution mobile sensing and BIGDATA. J. Eng. Mech. **142**(5), 4016019 (2016)
24. González, A., O'brien, E.J., Li, Y.-Y., Cashell, K.: The use of vehicle acceleration measurements to estimate road roughness. Veh. Syst. Dyn. **46**(6), 483–499 (2008)
25. Kong, X., Cai, C.S., Kong, B.: Numerically extracting bridge modal properties from dynamic responses of moving vehicles. J. Eng. Mech. **142**(2011), 4016025 (2016)
26. Huang, D., Wang, T.-L.: Impact analysis of cable-stayed bridges. Comput. Struct. **43**(5), 897–908 (1992)
27. McNeill, S.: Blind Modal Identification (BMID) toolbox. MATLAB (2011)
28. McNeill, S.I., Zimmerman, D.C.: A framework for blind modal identification using joint; approximate diagonalization: Mechanical Systems and Signal Processing. **22**(7), 1526–1548 (2008)
29. Chang, M., Pakzad, S.N.: Optimal sensor placement for modal Identi fi cation of bridge systems considering number of sensing nodes. J. Bridg. Eng. **19**(6), 1–10 (2014)
30. Chang, M., Pakzad, S.N.: Optimal sensor configuration for flexible structures with multi-dimensional mode shapes. Smart Mater. Struct. **24**(5), 55012 (2015)
31. Valeti, B., Matarazzo, T.J., Pakzad, S.N.: Experimental study on wireless mobile sensor configurations for output-only modal identification of a beam testbed. In: Sensors and Instrumentation, vol. 5, pp. 71–77. Springer, Cham (2017)
32. Matarazzo, T.J., Pakzad, S.N.: Sensitivity metrics for maximum likelihood system identification. ASCE-ASME J. Risk Uncertain. Eng. Syst. Part A Civ. Eng. **2**, B4015002 (2015)