An Introduction of a Robust OMA Method: CoS-SSI and Its Performance Evaluation through the Simulation and a Case Study

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Operational modal analysis (OMA) is a powerful vibration analysis tool and widely used for structural health monitoring (SHM) of various system systems such as vehicles and civil structures. Most of the current OMA methods such as pick-picking, frequency domain decomposition, natural excitation technique, stochastic subspace identification (SSI), and so on are under the assumption of white noise excitation and system linearity. However, this assumption can be desecrated by inherent system nonlinearities and variable operating conditions, which often degrades the performance of these OMA methods in that the modal identification results show high fluctuations. To overcome this deficiency, an improved OMA method based on SSI has been proposed in this paper to make it suitable for systems with strong nonstationary vibration responses and nonlinearity. This novel method is denoted as correlation signal subset-based SSI (CoS-SSI) as it divides correlation signals from the system responses into several subsets based on their magnitudes; then, the average correlation signals with respective to each subset are taken into as the inputs of the SSI method. The performance of CoS-SSI was evaluated by a simulation case and was validated through an experimental study in a further step. The results indicate that CoS-SSI method is effective in handling nonstationary signals with low signal to noise ratio (SNR) to accurately identify modal parameters from a fairly complex system, which demonstrates the potential of this method to be employed for SHM.

1. Introduction

Operational modal analysis (OMA) is, in fact, not really a new discipline. The beginning of OMA could be going back to the sixties and early seventies, which was developed along with the experimental modal analysis (EMA) [1]. However, OMA has been developed rapidly since the last two decades. One main reason for this is the availability of a large quantity of new powerful system identification techniques, which are the basis of OMA approaches available as a complementary tool [2–7]. Another reason is the rapid development of computer technology, which can compute the mass measured data in less time. Compared to EMA, the OMA has attracted a more considerable attention in mechanical engineering, aerospace engineering, and civil engineering since 1990s due to its many aspects. The main advantages of OMA are highlighted as follows [5, 8–10]:

(1) OMA is cheaper and faster to conduct since it only measures the responses
(2) The dynamic characteristics of the whole structural system can be obtained instead of its small parts
(3) A linear model of structural systems under operational conditions can be obtained since the random excitations are of broadband in nature
(4) OMA is suitable for complex and complicated structures due to the fact that the close modes can be identified through multi-input/multioutput (MIMO) modal identification algorithm

Because of these advantages, there are numerous OMA methods that have been developed in last decades. Generally, they can be classified into two categories: frequency domain (FD) and time domain (TD). The earliest FD technique is
based on the power spectrum density (PSD) peak-picking algorithm. The natural frequencies are directly obtained from the choice of peaks in the PSD graph. The peak-picking technique has proved its effectiveness in the modal identification method when system’s modes are well separated [4, 5]. This technique is simple to use. However, it has less accuracy because of the limitation of the frequency resolution in the PSD spectrum [4]. Therefore, peak-picking technique is unsuitable for the modal identification of the system with close modes [5]. However, the realistic complex structures are always encountered with close modes. Consequently, a new FD technique, named frequency domain decomposition (FDD), was developed to meet the challenge of the identification of the close modes [11]. In FDD, the response is derived into a set of single-degree-of-freedom systems by introducing a decomposition of the spectral density function matrix. The major drawback of the FDD is that it can only estimate the modal frequencies and the mode shapes but not the damping ratios. In order to extract the damping ratio, an enhanced FDD (EFDD) was then proposed [12]. The EFDD method extracts the damping of a particular mode by computing the autocorrelation and cross-correlation functions. However, all of the referred methods are under assumptions that the input signals are stationary Gaussian white noise and the structure is very lightly damped.

Besides the FD techniques, the TD techniques were also developed very quickly in the last decades. For instance, the natural excitation technique (NExT) is a popular and powerful TD method, which was proposed in 1990s [13]. It is based on the principal that the correlation functions can be expressed as the sum of exponentially decayed sinusoids assuming the ambient excitation as a white noise. The correlation functions perform the similar role like the impulse response functions in EMA, which consists of the information of the modal parameters [5, 14]. On the basis of this principle, some other traditional EMA techniques such as polynomial reference complex exponential (PRCE), Ibrahim time domain (EITD), and eigen realization algorithm (ERA) were also successfully extended and applied for the OMA.

Furthermore, stochastic subspace identification (SSI) method is another widely employed TD technique for OMA. It was proposed as an extension of the subspace state-space system identification method [5]. A systematic description of SSI and its applications can be found in [15–17]. However, the SSI method follows the same assumption like other OMA techniques; the excitations have to be stationary. Yet this is not always true for the field test of OMA. For example, the vehicle responses are always nonstationary resulted by frequently acceleration and deceleration. In addition, road humps and nonlinearity will also lead nonstationarity of the vehicle responses. In order to meet the challenge of nonstationarity, some improved SSI methods were proposed by the combining traditional SSI method with other methods, or preprocessing the measured responses before applying them in the SSI. For instance, empirical mode decomposition (EMD) was combined with SSI to extract modal parameters of civil structure from nonstationary signals [18]. What is more, a preprocess step was conducted in [19–21] by averaging the obtained correlation signals, which is denoted as average correlation signal-based SSI (ACS-SSI). The effectiveness of ACS-SSI has been proved by the experimental study of the extraction of the modal parameters of a chassis frame of a heavy-duty dump vehicle under normal operational condition.

Because of the effectiveness of the ACS-SSI method, it was employed to identify the modal parameters related to the vehicle suspension system. However, it was found that the ACS-SSI method was unable to accurately extract the target modal parameters due to the severe excitation condition. Consequently, a new method is needed to extract the modal parameters linked to the suspension parameters. In this study, the main objective of this paper is to present a novel method based on the ACS-SSI method [19, 20], denoted as the correlation subset-based SSI (CoS-SSI), for OMA of system under high noise scenery and with extreme nonstationary responses.

The rest of this paper has been divided into four sections. Section 2 outlines the enhanced method, CoS-SSI. Section 3 verifies the performance of this method through a vibration simulation of a typical 3-DOF system and Section 4 presents an experimental investigation of CoS-SSI to validate the simulation results. Finally, the conclusions are given in Section 5.

2. CoS-SSI Method

As referred previously, most of the OMA techniques were developed under the assumption that the measured responses are stationary. However, the field-monitored data are usually nonstationary such as the platform under the wave impacts and the bridge with the time-varying traffic loading [22]. The nonstationary responses will result in the variation of identified modal parameters from time to time, which may cause the monitoring process to be unreliable in many cases. Moreover, the nonstationary signals may lead to time-varying frequency contents characterized by modal components participating at different times and hence, part of the modes could be missed [19, 22].

The nonstationary problem has been addressed in [23, 24] by introducing the correlation technique, which demonstrates that the nonstationary procedure can be transferred into the stationary problem if the correlation functions are evaluated at a fixed time instant. A theoretical justification can be found in [13, 25]. Based on this theory, a method employing the correlation signals and combined with the framework of covariance driven SSI (Cov-SSI), denoted as ACS-SSI, was proposed in [19, 20]. The main steps of ACS-SSI are listed as follows [19–21, 26]:

(1) Obtain K numbers of data segments from the measurements of l channels.

(2) Calculate the correlation functions of each segment for different channels. The correlation functions can be calculated as follows when the reference is p channel:
parameters can be obtained by merging the similar modal correlation signals as a full set. Finally, the system modal correlation signals are averaged rather than considering all subsets according to their amplitudes, and each subset of signal are effective in suppressing nonstationary effect, and particularly, if \( l \) channels of vibration signals have been collected and they have been segregated into \( K \) segments, yet \( K \times l^2 \) of correlation signal segments can be obtained. Each segment has an RMS value, consequently, an RMS value matrix is obtained and its size is \( K \times l^2 \). The next step is obtaining the minimum RMS value from each segment, and this will yield a vector with \( K \) elements. The follow-up step is to obtain the minimum and maximum values from the vector and then calculating the difference of the obtained values. After that, using the calculated difference value, divide the number of subsets by it to calculate the interval of correlation segments. Finally, all of correlation signal segments are categorized into different subsets according to the obtained interval. The value of subset number is always set at 3 or 4 considering the accuracy of identification and the calculation efficiency.

For clarity, the CoS-SSI method is further summarized with a flow chart, shown in Figure 1. The improvement of the steps made in this study is highlighted with red boxes. In this study, a simulation study has been carried out to verify the performance of this newly proposed method by comparing with classical Cov-SSI and ACS-SSI methods. Furthermore, an experimental study has also been conducted to validate the simulation model and to evaluate the effectiveness of this novel method.

In plenty of OMA progress, stabilization diagram (SD) is a popular and efficient tool to filter out the false modes. The SD is performed to check the consistency of the modal properties by setting threshold values for the frequency, damping ratio, and the modal assurance criterion (MAC) between two adjacent orders; only the mode which satisfies all of the three thresholds will be allowed to plot a point on the SD. Moreover, the system’s true modes will produce stable points but the spurious modes will not. The tolerance can be calculated based on the following equations:

\[
\frac{f_i - f_{i-1}}{f_i} \times 100\% < \epsilon_f, \\
\frac{\xi_i - \xi_{i-1}}{\xi_i} \times 100\% < \epsilon_\xi, \\
1 - \text{MAC}(i : i - 1) < \epsilon_{\text{MAC}},
\]

where \( f_i, \xi_i, \Psi_i \) are the frequencies, damping ratios, and mode shapes obtained when the Hankel matrix has \( i \) rows parameters identified by ACS-SSI with respective to each subset. Moreover, the merging step is performed according to the discrepancy of the identified frequencies and modal assurance criterion (MAC).

Furthermore, unlike ACS-SSI, the main contribution of the CoS-SSI is dividing the correlation signals into different subsets according to their magnitudes. This key step is fulfilled by calculating the root mean square (RMS) value of each correlation signal segment and later identifying the correlation signal segments that belong to the respective subsets based on those corresponding RMS values. Particularly, if \( l \) channels of vibration signals have been collected and they have been segregated into \( K \) segments, yet \( K \times l^2 \) of correlation signal segments can be obtained. Each segment has an RMS value, consequently, an RMS value matrix is obtained and its size is \( K \times l^2 \). The next step is obtaining the minimum RMS value from each segment, and this will yield a vector with \( K \) elements. The follow-up step is to obtain the minimum and maximum values from the vector and then calculating the difference of the obtained values. After that, using the calculated difference value, divide the number of subsets by it to calculate the interval of correlation segments. Finally, all of correlation signal segments are categorized into different subsets according to the obtained interval. The value of subset number is always set at 3 or 4 considering the accuracy of identification and the calculation efficiency.

Based on the above analysis, the deficiency of the ACS-SSI method is evident. Therefore, the performance of ACS-SSI has to be enhanced to make it suitable for extreme nonstationary and quasi-nonlinear scenarios. In this paper, a novel method “correlation subset-based SSI” (CoS-SSI) was proposed which is based on the algorithm of ACS-SSI. Although ACS-SSI has deficiency, it has been proved that the average step conducted to the correlation signals calculated from the short segments of signal are effective in suppressing nonstationary effect, and that is why the same step is applied in the CoS-SSI method.

However, the correlation signals are divided into several subsets according to their amplitudes, and each subset of correlations signals are averaged rather than considering all correlation signals as a full set. Finally, the system modal parameters can be obtained by merging the similar modal correlation signals as a full set. Moreover, the merging step is performed according to the discrepancy of the identified frequencies and modal assurance criterion (MAC).
(orders) and $\varepsilon_f, \varepsilon_{\xi}, \varepsilon_{\text{MAC}}$ are the threshold (tolerance) values for the true modes. In this study, $\varepsilon_f, \varepsilon_{\xi}, \varepsilon_{\text{MAC}}$ were set at the values of 0.1, 0.2, and 0.5, respectively. Finally, the system’s real modes can be identified based on adequate stable points in the SD. The percentage of the stable points over the calculated number of orders is performed as the second threshold to indicate the corresponding mode with adequate stable points to be chosen as true or false one.

3. Numerical Simulation

3.1. 3-DOF Model Description. In this section, a classical 3-DOF vibration system, shown in Figure 2, was employed to generate simulation signals with a different level of noise to evaluate the performance of the proposed scheme by comparing with traditional Cov-SSI and ACS-SSI methods. The parameters for the 3-DOF system are of $m_1 = m_2 = m_3 = 200$ kg, $k_1 = k_2 = k_3 = 1.96 \times 10^6$ N/m, and $c_1 = c_2 = c_3 = 1.0 \times 10^3$ Ns/m; the theoretical modal parameters such as natural frequencies and damping ratios of this system can be calculated by using the parameters tabulated in Table 1.

In the simulation case, the 3-DOF system has been excited by three independent random inputs from a band-pass stationary white noise and a number of multiple random impulsive impacts. The impulsive excitations attempt to mimic the occasionally pulse inputs in real applications, such as the bump on the road. The responses $y(k)$ of this 3-DOF vibration system can be obtained through the “lsim” function in MATLAB. Moreover, the responses $y(k)$ of this system add more random signals to mimic the measurement noise, shown the following equation:

$$y_n(k) = y(k) + \delta \sigma(k),$$  

(4)

where $\sigma(k)$ is a band-pass white noise with $\sigma(0, 1)$ and the amplitude factor of measurement noise is defined in equation (5). It allows the performance of CoS-SSI to be evaluated under various scenarios that the output signals with different signal to noise ratios (SNRs).

$$\delta = \frac{\sum_{k=1}^{N} y(k)^2}{\text{SNR} \sum_{k=1}^{N} \sigma(k)^2}$$  

(5)

According to the theoretical resonance frequency of the third mode, the sampling frequency for the numerically solving system model was set at 500 Hz and sampling time was 60 s for each occasion. An example of the acceleration
responses of the 3-DOF system with measurement noise is shown in Figure 3. The mean values of every 2 seconds (1000 points) of the responses were calculated when the SNR was 10. It can be seen from Figure 3 that the mean values are changed over the time, which indicates the nonstationarity characteristic of the response signals.

The corresponding power spectrum density (PSD) of each block has been presented under the time-domain signals. It shows that only the first and second modes at the frequencies of 7.06 Hz and 19.65 Hz are clear, whereas the third mode is not that much prominent due to the damping ratio is higher (shown in Table 1). Moreover, it can be seen from the PSD of SNR = 0.5 that the noise has its effect on the energy distribution. Although the main peak values have not been affected, the second and third modes of \( m_2 \) have been submerged. Based on this result, it is reasonable to suppose that the noise may cause the modal parameters hard to be identified.

### Table 1: Theoretical modal parameters of a 3-DOF system.

|                | Mode 1 | Mode 2 | Mode 3 |
|----------------|--------|--------|--------|
| **Frequency**  | 7.01 Hz| 19.65 Hz| 28.39 Hz|
| **Damping ratio** | 1.12% | 3.15% | 4.55% |

In this section, to illustrate the superiority of CoS-SSI, the other two methods, Cov-SSI and ACS-SSI methods, are also employed in this simulation case. For the Cov-SSI, the dataset used to identify the modal parameters is of 60 seconds time duration for the 3-DOF system with measurement noise; the sampling frequency is 500 Hz. Apart from that, twenty more Monte Carlo simulations were carried out to generate the sufficient signals for modal parameters identification by the ACS-SSI and the CoS-SSI methods. Moreover, the correlation signals were calculated in each Monte Carlo simulation and therefore, twenty correlation signal segments were obtained. For the ACS-SSI, the twenty segments were averaged in single time, and then the averaged signals were employed to identify the modal parameters. However, as referred previously, the ensemble average might loss some significant signatures of the correlation signals with small amplitudes. Therefore, the twenty segments of correlation signals were divided into three subsets according to their magnitudes in the CoS-SSI, and the modal parameters were identified with respective to each subset of correlation signals. The SD identified by the three methods for the 3-DOF system under two SNR scenarios, SNR = 10 and 0.5, are presented in Figures 4–6, respectively.

It can be seen from Figures 4(a) and 5(a) that Cov-SSI and ACS-SSI have the ability to identify three relative stable modes when the SNR is 10. However, the SDs identified by CoS-SSI are messier than the previous two, which can be seen from Figure 6. These results might be caused by the classification of correlation signals before the averaging step which improved the SNR in a further step; the signals quality has been improved greatly. Therefore, the threshold should be stricter (with smaller value). It implies that CoS-SSI has no superiority when the signal quality is good. However, the advantage of CoS-SSI can be illustrated with poor quality signals (SNR = 0.5). The SDs identified by the three methods when the SNR is 0.5 are presented in Figures 4(b) and 5(b) and Figure 6. CoS-SSI are messier than the previous two, which can be seen from Figure 6(b) that Cov-SSI is unable to identify any stable modes. From Figure 5(b), it can be seen that ACS-SSI has the ability to identify first two stable modes, whereas the third mode is unstable. In contrast, CoS-SSI has identified three relative stable modes in the three subsets.

As referred earlier, a second threshold is set up to filter out the spurious modes. In this simulation case, 60 orders (rows) of the Hankel matrix are calculated, which can be seen from the left-y axe. The stable modes are chosen as the percentage of stable points over 50% of the SDs for Cov-SSI and ACS-SSI; this threshold for CoS-SSI is stricter which is set at 70%. An example of the second threshold result identified by Cov-SSI of the signal with SNR = 10 is shown in Figure 7.

Based on these two thresholds, the natural frequency and damping ratio identified by Cov-SSI, ACS-SSI, and CoS-SSI methods are listed in Tables 2–4, respectively. Moreover, the identification errors compared with the theoretical values are also listed in the tables. There are three noticeable things that can be found in the three tables. The first one is that the CoS-SSI cannot identify any mode when the SNR is 0.5; the second one is that the ACS-SSI can only identify first two modes but not the third mode under the same noise condition; and the third thing is that CoS-SSI has the ability to identify all the three modes with the acceptable errors.

In order to better illustrate the identification results, the identification errors of frequency and damping are presented in bar figures, which are shown in Figures 8 and 9, respectively. It can be seen from Figure 8(a) that the frequency identification errors are extremely small. Particularly, when the SNR is 10, most of the frequency identification errors are below 1%. Although the frequency identification errors from CoS-SSI are bigger than those of
ACS-SSI, the errors are still quite small, which are around 1.5%. The main reason for the bigger error of frequency identification from CoS-SSI is the average step accounted with less signals due to the signals are divided into three groups according to their amplitudes. Moreover, it can be seen from Figure 8(b) that the frequency identification accuracy of ACS-SSI and CoS-SSI methods has not been affected regardless of the measurement noise added.
Figure 6: Stabilization diagram of CoS-SSI. (a1) CoS-SSI (SNR = 10, J = 1/1st subset). (a2) CoS-SSI (SNR = 10, J = 2/2nd subset). (a3) CoS-SSI (SNR = 10, J = 3/3rd subset). (b1) CoS-SSI (SNR = 0.5, J = 1/1st subset). (b2) CoS-SSI (SNR = 0.5, J = 2/2nd subset). (b3) CoS-SSI (SNR = 0.5, J = 3/3rd subset).

Figure 7: Example of selecting modes by the rate of stable points over orders (CoS-SSI, SNR = 10).

Table 2: Cov-SSI results.

| Mode 1 | Mode 2 | Mode 3 |
|-------|-------|-------|
| $f_1$ (Hz) | Error ($f$) | $\xi_1$ Error ($\xi$) | $f_2$ (Hz) | Error ($f$) | $\xi_2$ Error ($\xi$) | $f_3$ (Hz) | Error ($f$) | $\xi_3$ Error ($\xi$) |
| Theoretical value | 7.0129 | Null | 1.12% | Null | 19.6468 | Null | 3.15% | Null | 28.3904 | Null | 4.55% | Null |
| SNR = 10 | 7.0308 | 0.37% | 1.25% | 11.61% | 19.6663 | 0.09% | 3.11% | 1.27% | 28.4377 | 0.17% | 4.3% | 5.49% |
| SNR = 0.5 | Null | Null | Null | Null | Null | Null | Null | Null | Null | Null | Null | Null |

Table 3: ACS-SSI results.

| Mode 1 | Mode 2 | Mode 3 |
|-------|-------|-------|
| $f_1$ (Hz) | Error ($f$) | $\xi_1$ Error ($\xi$) | $f_2$ (Hz) | Error ($f$) | $\xi_2$ Error ($\xi$) | $f_3$ (Hz) | Error ($f$) | $\xi_3$ Error ($\xi$) |
| Theoretical value | 7.0119 | Null | 1.12% | Null | 19.6468 | Null | 3.15% | Null | 28.3904 | Null | 4.55% | Null |
| SNR = 10 | 7.0090 | 0.04% | 1.08% | 3.57% | 19.6889 | 0.21% | 3.29% | 4.44% | 28.3172 | 0.26% | 4.81% | 5.71% |
| SNR = 0.5 | 7.0093 | 0.04% | 1.19% | 6.25% | 19.6797 | 0.17% | 3.41% | 8.25% | Null | Null | Null | Null |
However, the damping ratios are identified with huge errors in spite of the signal quality, which can be seen in Figure 9. This is reasonable because the damping estimation is a common challenge for all the system identification methods. In addition, it is evident from the theoretical results that the value of damping ratios are much smaller than the frequency; this could also lead the error of damping ratios becoming much more evident, especially for the first mode. Therefore, the damping ratio will not be chosen as a vital reference for structural health monitoring (SHM).

However, the mode shape is the most significant index for SHM whenever we adopt any modal parameters identification methods. It is well-known that MAC values are widely employed to compare two mode shapes to see

| Table 4: CoS-SSI results. |
|---------------------------|
| | Mode 1 | | Mode 2 | | Mode 3 |
| | $f_1$ (Hz) | Error ($f_1$) | $\xi_1$ | Error ($\xi_1$) | $f_2$ (Hz) | Error ($f_2$) | $\xi_2$ | Error ($\xi_2$) | $f_3$ (Hz) | Error ($f_3$) | $\xi_3$ | Error ($\xi_3$) |
| Theoretical value | 7.0119 | Null | 1.12% | Null | 19.6468 | 1.60% | 4.45% | 41.27% | 28.5183 | 0.45% | 6.53% | 43.52% |
| SNR = 10 | S1 | 7.0275 | 0.22% | 2.17% | 93.75% | 19.3324 | 1.60% | 4.45% | 41.27% | 28.5183 | 0.45% | 6.53% | 43.52% |
| S2 | 7.0118 | 0 | 1.97% | 75.89% | 19.3377 | 1.57% | 5.91% | 87.62% | 28.5781 | 0.66% | 6.71% | 47.47% |
| S3 | 7.0405 | 0.41% | 5.17% | 361.61% | 19.3322 | 1.6% | 3.92% | 24.44% | 28.5076 | 0.41% | 5.83% | 28.13% |
| | S1 | 7.0170 | 0.07% | 3.47% | 209.82% | 19.5947 | 0.27% | 5.14% | 63.17% | 28.4288 | 0.14% | 6.53% | 43.52% |
| S2 | 7.0234 | 0.16% | 2.58% | 130.36% | 19.5935 | 0.27% | 3.74% | 18.73% | 28.5125 | 0.43% | 3.50% | 23.08% |
| S3 | 7.0220 | 0.14% | 4.45% | 297.32% | 19.5887 | 0.30% | 3.51% | 11.43% | 28.4736 | 0.29% | 5.53% | 21.54% |

![Figure 8: Identified frequency errors. (a) Identified frequency errors (SNR = 10). (b) Identified frequency errors (SNR = 0.5).](image1)

![Figure 9: Identified damping errors. (a) Identified damping errors (SNR = 10). (b) Identified damping errors (SNR = 0.5).](image2)
whether they are close or not. In this simulation study, all of the identified mode shapes are illustrated by the MAC values by comparing with the theoretical mode shapes, shown in Figures 10–12. From these figures, it can be seen that all of the MAC values for the identified modes are close to 1. Furthermore, the result of ACS-SSI can only identify two modes when the SNR is 0.5 and has been illustrated in Figure 11. Based on these results, it could recognise the powerful ability of the MAC value to indicate the mode shapes.

All of the three methods have been evaluated by using a 3-DOF vibration system. It seems highly probable that CoS-SSI is superior to other two methods, especially treating high noise signals; however, signals collected under operational conditions always contained with high noise.

4. Experiment Study

4.1. Experiment Setup. The experiments carried out in this paper are to identify the vehicle suspension-related modal parameters by collecting the vibration signal from a car body at four corners. The experimental car is a commercial car, and its model is Vauxhall Zafira. The signals were collected during car running on a traditional UK rustic road. Moreover, four accelerometers were employed to collect the vibration signals from the vehicle body which caused by the road excitation. The four transducers are piezoelectric accelerometers which are produced by SINOCERA and the model is CA-YD-185. This is a widely used kind of transducer because of its wide frequency measurement range, which is from 0.5 Hz to 5000 Hz. A four-channel data acquisition system and a laptop were adopted to collect and store the signals, respectively. The data acquisition system model is YE6231 and is also manufactured by SINOCERA with maximum sampling frequency of 96,000 Hz.

In this experiment, the accelerometers were mounted at the four corners of the car, and they were kept much close to the connection point of suspension. This is to obtain better quality vibration signals from the suspension system which are related to the road excitation. The tested car and a schematic of data acquisition system are presented in Figure 13.

4.2. Signal Characteristics. The purpose of the method proposed in this paper is to identify the modal parameters of vehicle under running condition. Therefore, the data were collected when the vehicle was driven on the typical UK suburb roads with speed limits from 20 to 40 miles/hr. In order to confirm no loss of information in the modal identification process, the sampling frequency was set much higher than the requirement of Nyquist sampling theory; the sampling frequency was 4000 Hz, and each test sample was recorded with the time duration of 240 s. Moreover, the test was repeated 4 times by driving on the same road section. Although the sensors were installed close to the suspension, the collected signals still contained high noise because this is a field test and there are thousands of reasons that can introduce unwanted measurement noise. Furthermore, the vehicle was running on the real road, not on a test platform; therefore, the speed was not always constant. The changing speed will cause nonstationary vibration. In addition, the random big excitations such as the hump on the road will also result in nonstationary responses of the vehicle.

An example of the collected signals is presented in Figure 14, and the corresponding power spectrum densities (PSD) were presented below. From the time-domain waveform analysis, it can be seen that the car body vibration is highly nonstationary. In addition, it can be seen from the PSD that the main power of the signal is around the frequency of 2 Hz, and a small peak appears around the frequency of 12 Hz, which are related to the car body and the wheel bounce, respectively. Moreover, it is noticeable from the PSD that the vibration amplitudes from the front part of the vehicle are smaller than its rear part. The main reason is the engine located in the front part of the vehicle. As a result, the pitch mode of the vehicle is easier to be excited.

4.3. Identification Results. In this section, only ACS-SSI and CoS-SSI methods are applied to identify the modal parameters of the car when it was in normal operation. As referred previously, the vehicle test was repeated four times with the sampled time duration of 240 s and sample rate of 4000 Hz. Firstly, the data of each test were segregated into six segments (40 s for each segment). Therefore, there are 24 (4 times × 6 segments = 24) data segments in total. Secondly, the correlation signals of each data segment were calculated. Then, for the ACS-SSI method, the correlation signals were averaged in a single time; for the CoS-SSI, the correlation signals were categorised into three subsets according to their amplitudes, and each subset was averaged. During the identification process of these two methods, the same threshold ($\varepsilon_1, \varepsilon_2, \varepsilon_{MAC}$) was set when developing the SDs; $\varepsilon_1, \varepsilon_2, \varepsilon_{MAC}$ were set at 0.1, 0.2, and 0.5, respectively. Moreover, the orders (rows) of Hankel matrix were 100 to develop the SDs.

The SD identified by ACS-SSI is presented in Figure 15(a). It is apparent that two relative stable modes...
around 2 Hz were identified. Figure 15(b) shows the rate of identified stable points over the calculated orders. It can be observed from Figure 15(b) that the stable points for the first two modes are at 60% and 40%, respectively. This indicated that the second mode cannot be identified when we set the second threshold at 50% which is the same as the simulation case. In order to present the mode shapes of the two relative stable modes, the second threshold was set at 40% and the ACS-SSI identified modal parameters are given in Figure 16. These two modes seem like pitch. However, the first mode should bounce according to the theoretical modal parameters [27]. The reason for it looks like pitch mode could be because of the front part of the vehicle is heavier and therefore it has smaller amplitude vibration. Moreover, the nonstationary responses and high measurement noise will also have effect on the identified mode shapes.

In the second place, the SDs identified by CoS-SSI are presented in Figures 17(a1), 17(b1), and 17(c1). It can be seen that the SDs identified from the first two subsets are bit messier than the third one. Furthermore, the rate of the
stable modes over calculated orders is presented in Figures 17(a2), 17(b2), and 17(c2). It can be seen that the rates of the stable modes are much higher than the rates of modes identified by ACS-SSI. Therefore, a higher second threshold can be selected to obtain the target modes, which means the identified results are more reliable than the results identified by the ACS-SSI method. At the end, the second threshold value was found at 80%. It can be seen from Figures 17(a2), 17(b2), and 17(c2) that a mode around the frequency of 1.58 Hz was selected in the first subset, and two modes around 2.34 Hz and 9.02 Hz were identified in the second subset. Furthermore, the modes around 1.58 Hz and 2.06 Hz were identified in the third subset. The corresponding mode shapes identified from each subset are shown in Figure 18. It can be observed that the mode identified from the first subset is similar to the bounce mode
Figure 16: Modal parameters identified by ACS-SSI. (a) 1.64 Hz, 21%. (b) 2.133 Hz, 17%.

Figure 17: Stabilization diagram identified by CoS-SSI. (a1) SD of CoS-SSI (J = 1/1st subset). (a2) Selecting mode by the rate of the stable frequency over orders for on road vehicle modal identification (J = 1). (b1) SD of CoS-SSI (J = 2/2nd subset). (b2) Selecting mode by the rate of the stable frequency over orders for on road vehicle modal identification (J = 2). (c1) SD of CoS-SSI (J = 3/3rd subset). (c2) Selecting mode by the rate of the stable frequency over orders for on road vehicle modal identification (J = 3).

Figure 18: Modal parameters identified by CoS-SSI. (a) J = 1(1st subset). (b) J = 2(2nd subset). (c) J = 3(3rd subset).
identified from third subset; the first mode identified from the second subset is similar to the pitch mode identified from the last subset. Furthermore, it can be seen that a mode around 9 Hz was identified in the second subset which can be linked to the wheel bounce according to theoretical dynamic analysis in [27].

What is more, roll is a significant mode in the theoretical vertical vehicle dynamic analysis. However, it is noticeable that the roll mode has not appeared in the identification results. In view of the vehicle and road design requirements, the roll mode has to be avoided for the safety. The results demonstrating no roll mode has illustrated the robustness of the proposed method in a further step. Consequently, the CoS-SSI method has identified all of the vehicle suspension system-related modes under a high second threshold (80%), which indicates the reliability of the identified results.

5. Conclusions

An improved OMA method, denoted as CoS-SSI, was proposed in this paper to accurately identify the modal parameters when the system responses are highly nonstationary and contained high noise. As the inherent nonlinearity of engineering systems often results in nonstationary vibration responses due to changes in modal properties under different operating conditions, the method then categorizes such responses into a number of subsets based on energy levels and implement SSI subsequently on the ensemble averaged data for accurate and consistent identification. The performance of CoS-SSI was evaluated by a 3-DOF typical vibration system under various SNR conditions. Then, an experimental study of vehicle running on the practical suburb roads was carried out to verify the performance of CoS-SSI in a further step. Both simulation analysis and the experimental results provide compelling evidence that the CoS-SSI method is superior to the traditional Cov-SSI and ACS-SSI methods. In other words, the CoS-SSI method can provide a more accurate and reliable modal identification results when the structure is under severe situations; the accurate results ensure the reliability of the SHM.

Data Availability

The experimental data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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