A New Damage Detection Method for Bridge Condition Assessment in Structural Health Monitoring

Ayaho MIYAMOTO*
* Graduate School of Science & Engineering, Yamaguchi University
2-16-1 Tokiwadai, Ube 755-8611, Japan
E-mail: miya818@yamaguchi-u.ac.jp

Abstract. This paper introduces a newly proposed "State Representation Methodology (SRM)" and its application to bridge condition assessment based on the bridge monitoring data. The SRM is a novel tool that can provide some ideas and algorithms for data mining in the bridge monitoring system. The state of a system such as bridge structure can be obtained by a state variable that calculate from a State Representation Equation (SRE). A Kernel function method which plays an important role in the Support Vector Machines (SVM) is applied to get solutions of the SRE. In the computation of the SRE, it needs to be changed into a Large-Scale Linear Constraint Problem (LSLCP). A new compatible algorithm is therefore proposed for solving technique of the LSLCP. Before using the SRM, it is necessary that the system features need to extract from the complex responses observed data in the system. Consequently, a new time-frequency analysis tool, called Frequency Slice Wavelet Transform (FSWT), will be able to powerfully reveal a change of the characteristics in vibration signal. The FSWT produces five new properties in contrast with the traditional wavelet transform. Therefore, the paper will show the new method that can be used widely in signal processing. In this paper, it will also be introduced a general theory for the non-parametric description of the infrastructure system's state and will demonstrate how to apply the SRM to practical problems.

1. Introduction

In recently, structural health monitoring (SHM) has received an increasing attention in the field of deteriorating civil infrastructures, such as bridges, highway networks, etc [1]. Meanwhile, the condition assessment is becoming one of the most important issues in this field. A large size structure such as bridges produces a huge amount of monitoring data for every day, every month and every year. It becomes also an important thing that how to detect damages from such huge number of monitoring data, that is a big challenge for analysis to discover the damage information of a target structure. Furthermore, there are not only many kinds of sensor data, but also many undetermined factors in the system, such as the dynamic loads, ever-changing climate condition, and severe noise interference. At the same time, we cannot exactly find a model to describe any structure and a variety of data interrelationship in design stage or during any operating period. In generally, the large structure can be viewed as a system, and the large-scale systems theory or any other new methods can be employed to research the system. It is obvious that those large systems are a high-order nonlinear system. The nature exists a great of complex systems, many of them have some similar or not. At

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least, the description of a system state is an essential problem, and even a philosophical methodology problem [2].

Figure 1 shows that how important the condition assessment in SHM research. It is easy to understand from this figure that the practical condition assessment is still a basic problem in SHM research, although there are many literatures to study on the topics for SHM. In this paper, it will be focusing on to try to easy explanation of the analysis methods of condition assessment in SHM with comparison between traditional methods and a new proposed method which called "Sate Representation Methodology (SRM)"[3,4,5]. Then the main content of the paper is consisted from the basic theory (concept) of "Sate Representation Methodology (SRM)" to its applications to practical "Condition Assessment" for bridge structures.

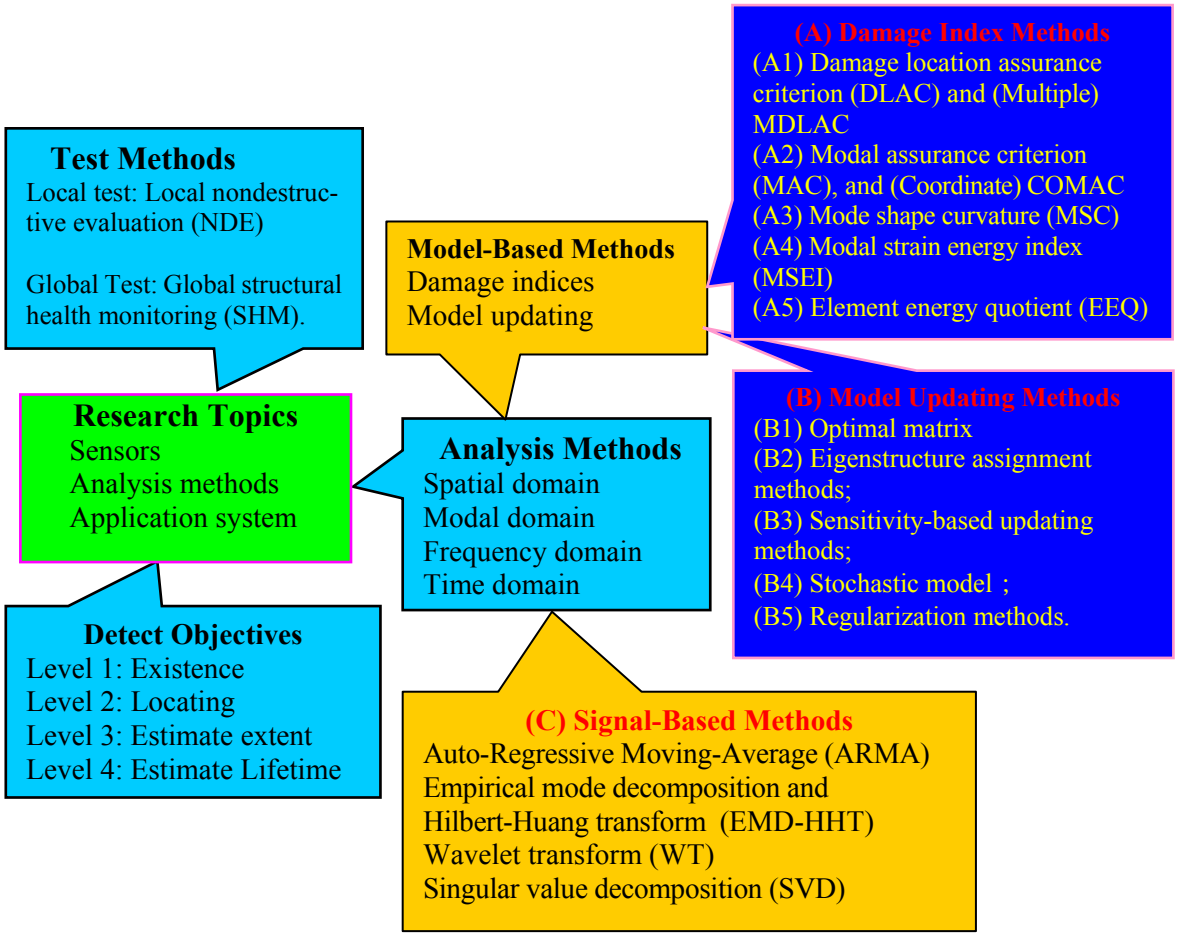

Figure 1. Summary of Data Analysis Methods for Condition Assessment in SHM Research

2. State Representation Methodology (SRM) for Bridge Condition Assessment

2.1 What is the SRM?

Here, we will be focusing on the structural health monitoring system (SHMS). Especially, how do we describe the probability state from the structure monitoring data? In another view, can we know more about what's happened & when the monitored signals have been changing, and what is the relationship between the system state and the sensor's signals? All of those about detecting and locating are very important for a practical SHMS. In this paper,

we will be able to give a new idea and systematic methods to describe and assess the structural state which called as the system **S**tate **R**epresentation **M**ethodology (SRM) [2,3]. Based on theoretical research of the SRM, we developed a systematic method to describe damage feature and state of structural system.

In a complex system such as bridge structures, it comes some common and basic questions as follows:

(1) What is the present state of a system ?
(2) How is it possible to build a model to describe the system state ?
(3) How is it possible to compare the state change of the system ?
(4) How is it possible to extract the state features of the system ?
(5) What kind of damages are occurring in the system ?
(6) How is it possible to locate a damage of the system ?

2.2 What is the State of a System?

The state of a system is interpreted as the overall response to its internal and external factors which essentially depend on the response of structure itself or structural properties and nature environment. Then, the quantitative assessment of the system state is the description for system responding to the exciting factors. If the responses satisfy the suitable values, the system state is considered as normal state, otherwise as abnormal (damaged) state. In usually circumstances or under normal use conditions, the system is in stable state, this means its state should be a constant, or fluctuation near a steady state. In general sense, we therefore assume that it is a steady random variable and it is usually obeyed the normal distribution.

[Assumption]: *The state of a system is a function of the system response to environmental exciting*

Obviously, this assumption has so natural sense. Nevertheless, we cannot use the response data directly in time domain because it is obvious time-varying signal. Therefore, we usually translate into the frequency domain or other transformation domain. This process is called features extracting. **Figure 2** shows the procedure of feature extracting, in where x is called the system feature vector, ζ is the state variable, λ is the system structure alias parameter. Therefore the state of a system can be described by the variable, ζ , and it should be a function about the system features that can be extracted from the responses to its various factors. In fact, the successful use of the SRM depends on the experimenter's ability to develop a suitable approximation for the system state function, $f(\cdot)$, which it is called "State Representation Function (SRF)". The SRF can be written as,

$$\zeta = f(\lambda, x) = 1 \tag{1}$$

The SRM tools mentioned in **Figure 2** will be introduced in Ref. [4].

2.3 System State Approximating

Figure 3 shows a basic idea for state variable expression by approximating methods. The following will analyze the main idea of the Kernel Function expression.

Let w is constant vector in R^n , called as system state support vector which is relative with the system structure parameters, we take the first-order model to approximate the Eq. (1) as the following:

$$1 =< w, x >= \sum_{k=1}^{n} w(k)x(k) \tag{2}$$

Use the Least Squares Estimators (LSE) method, it is easy to get the weight vector w; if the system has only one response feature vector h in its initial feature space (*IFS*), i.e. we assume that $h \in IFS \subset R^n$, the least squares solution of Eq. (2) should be:

$$w = \frac{h}{\|h\|^2} \tag{3}$$

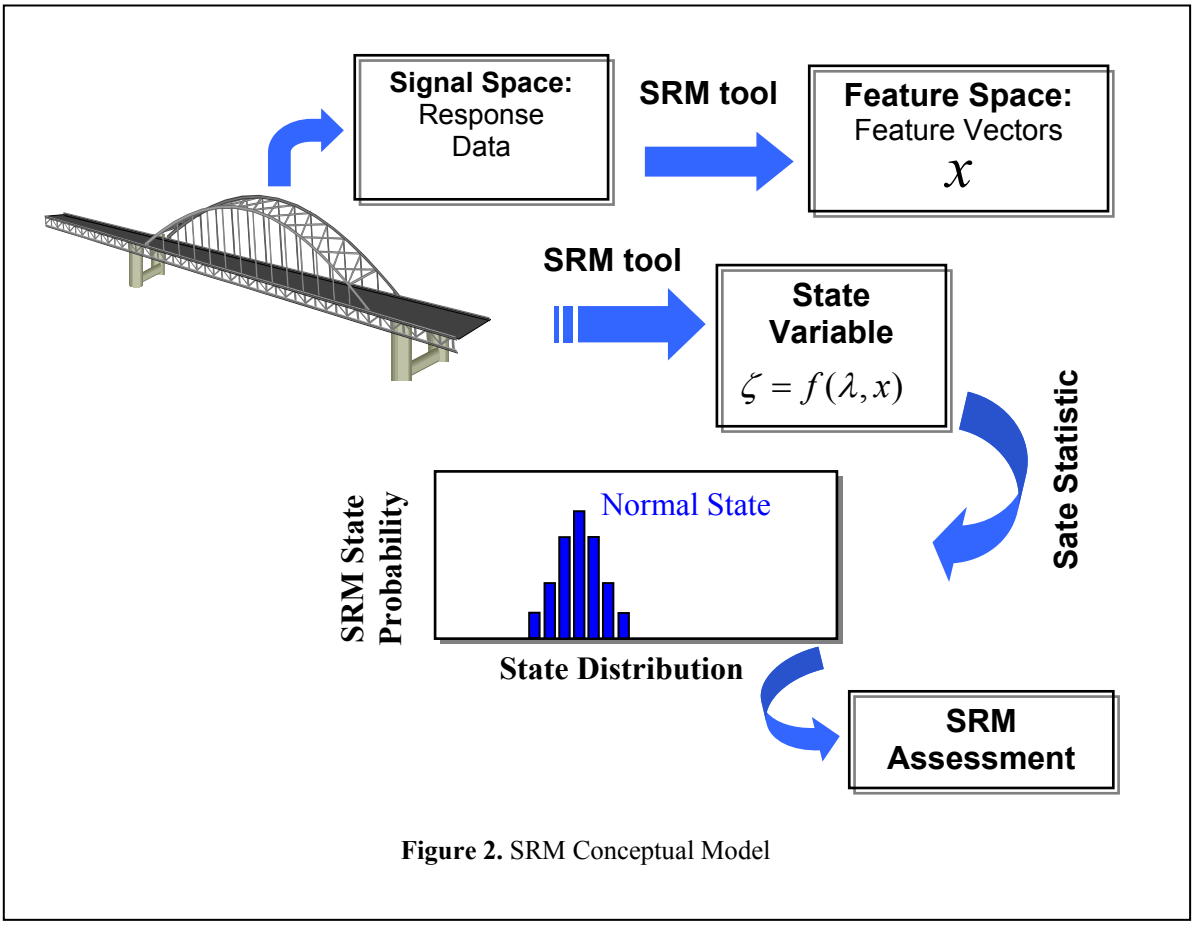

Figure 2. SRM Conceptual Model

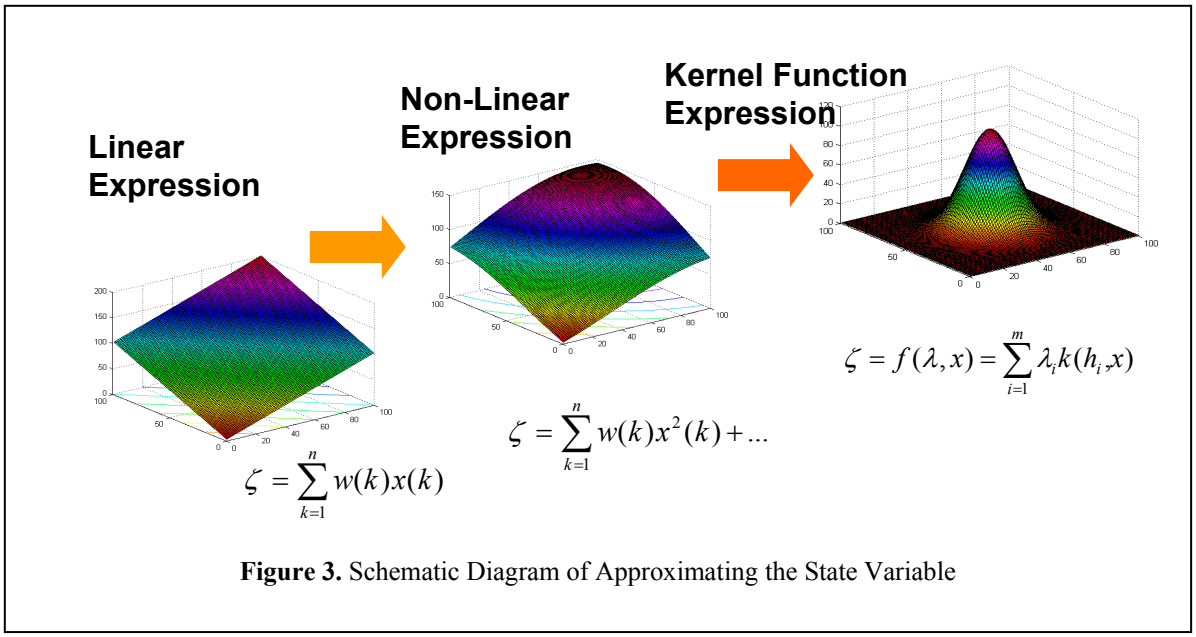

Figure 3. Schematic Diagram of Approximating the State Variable

However, we respectively take m feature vectors of *IFS,* the least squares solution respectively should be:

$$w_i = \frac{h_i}{\|h_i\|^2}, i = 1,2....m \tag{4}$$

Now let us think every response feature vector $h \in IFS$ as a projector of the current system state along with each feature direction, then we give them with a weight: $\lambda_i \geq 0$ and

$$\lambda_i \in (0,1),\ \sum_{i=1}^{m} \lambda_i = 1\ , w = \sum_{i=1}^{m} \lambda_i w_i = \sum_{i=1}^{m} \alpha_i h_i, \quad \alpha_i = \frac{\lambda_i}{\|h_i\|^2} \geq 0$$

Then,

$$1 =< w, x >=< \sum_{i=1}^{m} \alpha_i h_i, x >= \sum_{i=1}^{m} \alpha_i < h_i, x > \tag{5}$$

One can define a function included parameter vector α , as:

$$f(\alpha, x) = \sum_{i=1}^{m} \alpha_i < h_i, x > \tag{6}$$

Eq. (6) is called the first-order representation function of system state, it's a linear operator, where vector α is also called as system alias parameter or system state parameter, which is relative with the system structure. Note that Eq. (6) can be rewritten as,

$$f(\lambda, x) = \sum_{i=1}^{m} \lambda_i \frac{\|x\|}{\|h_i\|} < \frac{h_i}{\|h_i\|}, \frac{x}{\|x\|} > \qquad \sum_{i=1}^{m} \lambda_i = 1, \quad \lambda_i \geq 0 \tag{7}$$

If $\|h_i\| = \|x\|$ is always assumed, then we have,

$$f(\lambda, x) = \sum_{i=1}^{m} \lambda_i < \frac{h_i}{\|h_i\|}, \frac{x}{\|x\|} > \qquad \sum_{i=1}^{m} \lambda_i = 1, \quad \lambda_i \geq 0 \tag{8}$$

Then,

$$f(\lambda, x) \leq 1 \quad \text{for always} \tag{9}$$

Let $\overline{w} = \sum_{k=1}^{m} \lambda_k \frac{h_k}{\|h_k\|}$, then Eq. (8) can be rewritten as:

$$f(\overline{w}, x) =< \overline{w}, \frac{x}{\|x\|} > \tag{10}$$

The inner product $< \cdot >$ can be replaced by a Kernel Function form as follows. In generally, we can redefine $< s, x >, s \in X, x \in X$ as:

$$< s, x >=< \phi(s), \phi(x) >= k(s, x), s \in X, x \in X \tag{11}$$

where, X is a vector space. Here $k(s,x) =< \phi(s), \phi(x) >$ is called a Kernel Function. There are many choices for a Kernel Function $k(\cdot,\cdot)$. Here, the following Kernel Functions are recommended in [3,4,5].

$$k(s, x) = \exp(-\frac{d(s, x)}{\sigma^2}), \tag{12}$$

here, $d(s,x) = \sum_{i=1}^{n} \frac{(s_i - x_i)^2}{s_i + x_i}$ or $d(s,x) = (\sum_{i=1}^{n} |s_i - x_i|^p)^{1/p}$

$$k(s, x) = (s \cdot x)^d, \ (\|s\| = 1, \|x\| = 1) \tag{13}$$

Note that σ is called the SRM scale**.** In fact, the difference between two any objects is absolute on any scales, but their similarity is relative on any scale. Therefore, scale concept is important to study the difference between two states of a system. Subsequently, we can get state function in the Kernel Function form:

$$\zeta = f(\lambda, x) = \sum_{i}^{m} \lambda_i k(h_i, x) .$$

In order to satisfy that state should be a constant, we are able to define the following objective function:

$$\begin{aligned} &\min \quad \left\| (I - \frac{1}{m} ee^T) G\lambda \right\|^2 \\ &\text{Subject to} \quad \sum_i \lambda_i = 1, 0 \le \lambda_i \le 1, i = 1,2,3,....\text{m} \end{aligned} \tag{14}$$

$$\text{here,} \quad G = \begin{pmatrix} k(h_1,h_1), k(h_1,h_2), ...k(h_1,h_m) \\ k(h_2,h_1), k(h_2,h_2), ...k(h_2,h_m) \\ ..... \\ k(h_m,h_1), k(h_m,h_2), ...k(h_m,h_m) \end{pmatrix}$$

Then, we can get state function as following:

$$\zeta = f(\lambda, x) = \sum_{i}^{m} \lambda_i k(h_i, x) .$$

Eq. (14) can be illustrated as **Figure 4**, where *c* is constant for a system, and $c = \frac{1}{m} e^T G\lambda$. We can get the alias parameter λ of system structure, which is also called as the support vector in SVM [7,8,9].

Let the system be in state ζ in current time with feature vector *x*, i.e. $\zeta = f(\lambda, x)$. ζ has different value with different feature vector *x* because of the system complexity. We may not know how many state values a system has, but we usually assume ζ to be a normal probability distribution. Many statistics methods can be performed to estimate the probability distribution. Therefore, we can use in variety of statistic tests such as *F*-test and *t*-test etc. to assess the difference between ‘‘virgin’’ state and ‘‘damaged’’ state in the past time. By using a laboratory bridge monitoring system (LBMS) [6] to verify the SRM, experiments show that the SRM is available and steady to express the system state.

2.4 How Differences between the Existing Methods and the SRM?

Figure 5 shows that traditional methods based on frequency domain decomposition (FDD) are widely recognized as a simple method [5]. However, it tends to often lead to the loss of sensitivity and accuracy of damage detection, because the power spectrum of the measured responses could not be accurately estimated, particularly for high-damped systems and systems with severe modal interference and high noise. Meanwhile, there are some important questions in it: The natural frequency, corresponding mode shape and damping coefficient are usually changing very slowly when the bridge system is deteriorating in the early stage, in other words, the bridge health condition is always not sensitive with those parameters. At the same time, since a complex system include many structural parts, it has many frequency components, and they are interfered each other, so it is very difficult to use FDD to analyze a system in damage detection because it is impossible to get modal parameters exactly. Then we proposed a new method based on an overall view parameter to identify a system. In here, we assume that the system state is a dynamic variable, and a probability method with random

factors was introduced as a better method to describe its present state because it is always in many random conditions (factors).

Figure 6 shows the main principle of the proposed SRM. At first, it needs to change time domain data into the transformation domain features in the SRM. Then we are able to derive a system state variable in the feature space. Furthermore, we need to make the statistic probability distribution of the derived variable. Finally, the question of "condition assessment" of the present system becomes into a problem of "state assessment".

As stated above, among various damage detection methods, the vibration-based one is most widely used, the core idea is that vibration responses are directly relative with the physical structure and properties, such as mass, stiffness and boundary conditions, and those

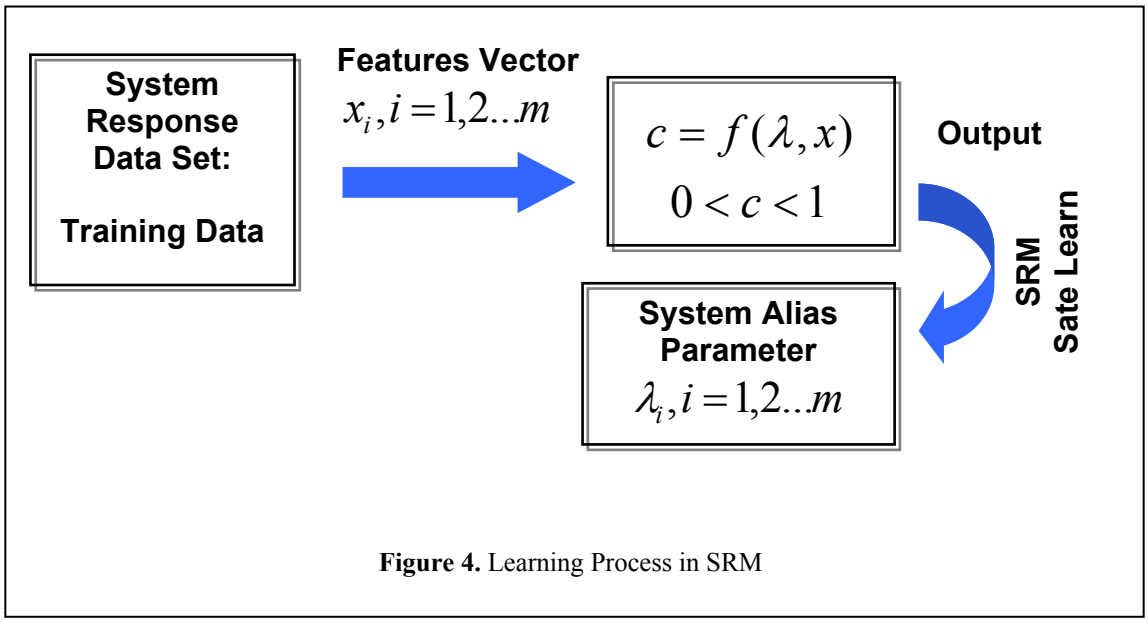

Figure 4. Learning Process in SRM

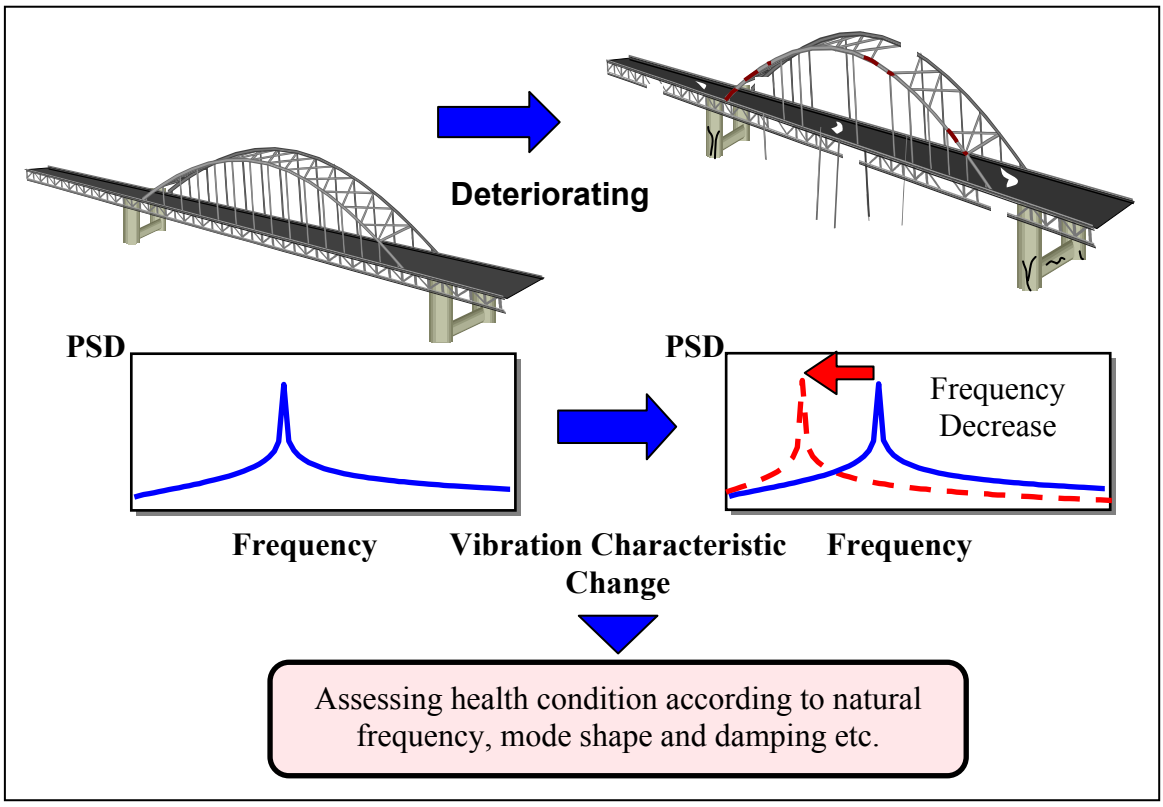

Figure 5. Frequency Domain Decomposition (FDD) Principle

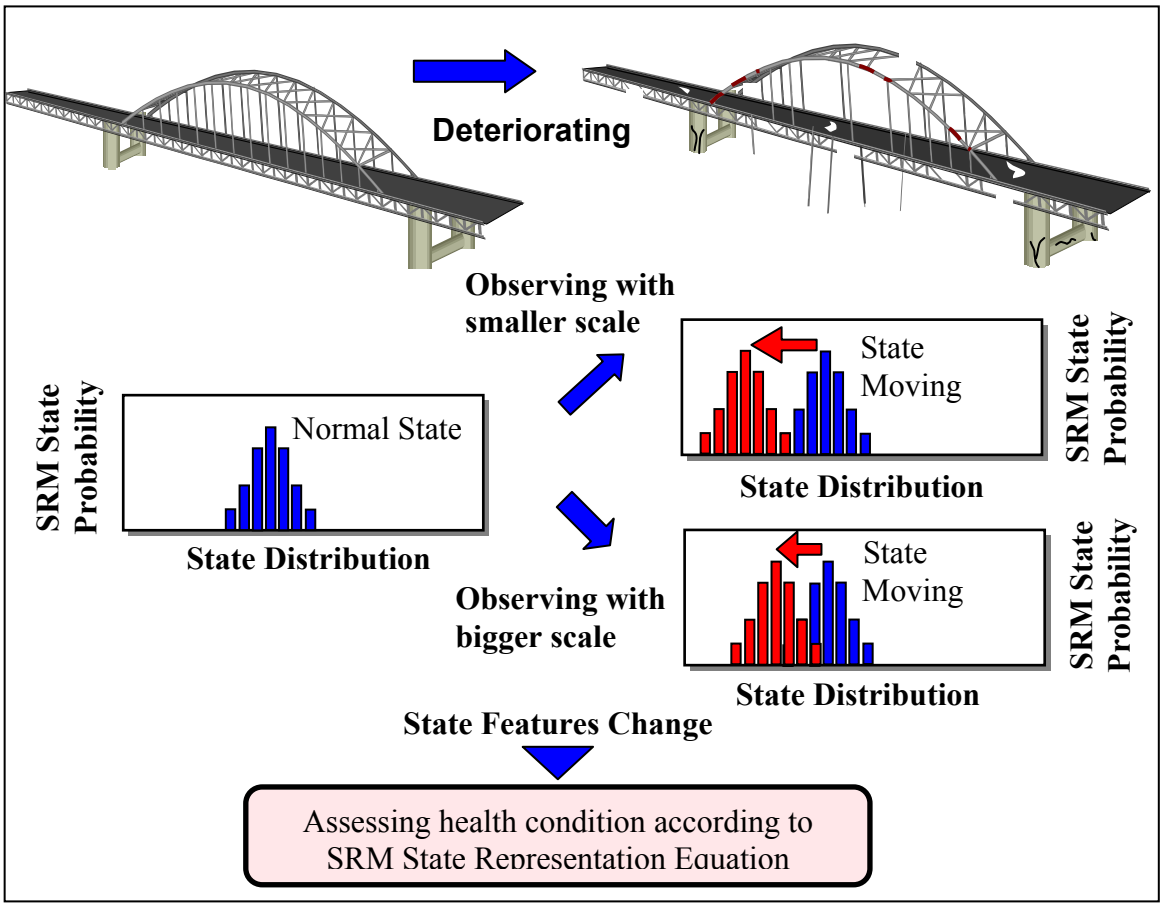

Figure 6. SRM Principle

changes of vibration responses can be used to characterize the structural damage. Although many intuitive and considerable research efforts have been devoted to it during the past decades, assessing structural damage in large-scale bridges still remains a challenging task for civil engineers. A research [6] shows that many factors can affect the assessed results, such as, the insensitive of modal properties to local damage of bridge structures, uncertainty and incompleteness in measurement data, modal variability arising from varying operational and environmental conditions, and modeling errors in the analytical model etc. Use of physics-based damage detection or model-based damage detection methods often lead to update a large number of damage parameters, especially when the structure has an abundance of structural members. Therefore they have to reduce their parameters. One problem which may arise with this method is that parameter reduction may identify the most damage-sensitive parameters but may fail to locate the damage correctly. At the same time, these same factors often lead to the ill-conditioning of model updating and damage detection problems, where small measurement noises could be magnified, this means that noise or complex factors can always corrupt the analysis accuracies. However, the sensitivity and the stability of a method are simultaneously important to the practical applicability. Meanwhile, many literatures don't consider these facts that the model updating condition is dynamic and our knowledge is an embedded process as the time ongoing. Therefore, not only requires the improving of approaches for model updating and damage detection, but also our methods should be built on a process of observation by means of continuously accumulated data. SRM gives the method driven by monitoring data or by experimental data in inspection. The SRM directly helps to know what is the difference between ''virgin'' state and ''damaged'' state after an observed time. A nonparametric structural damage detection methodology based on nonlinear system identification approaches is presented for the SHM.

3. SRM Application to Damage Detection

3.1 Basic Idea of System Feature

This section describes the basic concept of describing system state about SRM based on vibration equation. A general idea of nonparametric description will be the derivate from the governing equation of motion of structural system. We then can understand the aim of featuring system responses. A common-used vibration equation is written as:

$$Ms'' + Cs' + Ks = 0 \tag{15}$$

In Single Degree of Freedom (S-DOF) system, it is easy to determine the parameter mass *M*, damping coefficient *C*, and stiffness *K*. However, in general, it is very difficult for Multi-DOF (MDOF) complex system. From the vibration equation for S-DOF, the vibration frequency ω is relation with *M, K, C* parameter, and it can be written to be:

$$\omega^2 = \frac{K}{M} - \frac{C^2}{4M^2} \tag{16}$$

Follows that:

$$M = \frac{K \pm \sqrt{K^2 - (\omega C)^2}}{2\omega^2} \quad \text{or denoted as } M = f(K, C, \omega) \tag{17}$$

For MDOF, it can be expressed as:

$$\sum_i f(K_i, C_i, \omega_i) = M_{total} = \text{CONSTANT} \tag{18}$$

or

$$\sum_i \frac{1}{M_{total}} f(K_i, C_i, \omega_i) = 1, \quad \text{CONSTANT} \tag{18'}$$

Therefore, we call the vector $x = (\omega_1, \omega_2, ...\omega_n)$ as the response features of the system, and we also call the relative vector $\lambda \leftrightarrow (M_1, K_1, C_1, M_2, K_2, C_2, ...M_n, K_n, C_n)$ as the system structure parameters or alias variable of the system structure. Note that the system alias variable λ is relative but probably different with the real structural parameters $(M_1, K_1, C_1, M_2, K_2, C_2, ...M_n, K_n, C_n)$, and it is no necessary to know the real parameters, but λ is a function of these parameters. In a monitoring system, we usually only know the response data in time domain. With the aid of many transforms, such as Fourier transform, Wavelet transform, Laplace transform, and so on, we can get the feature vectors *x*, which is consist of the feature space of the system. However we don't know the system variable, λ. Here, the State Representation Function (SRF) can be written as mentioned before (Eq. (1)):

$$\zeta = f(\lambda, x) = 1 \tag{1'}$$

A Kernel Function tool is applied to get a solution of this equation, then we can get the estimation of variable, λ. Then we will be able to know the state variable, ζ of a system. **Figure 7** shows the basic principle of SRM methods.

3.2 Approximate Feature Vectors Problem

In Eq. (1'), the determination of the state variable depends on the system structure parameters and the system features. One of the main idea in the SRM is to understand the system inner

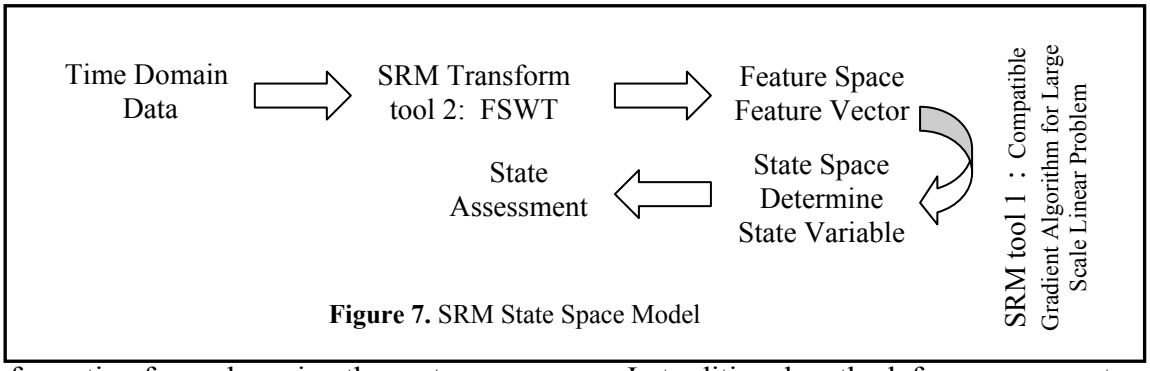

Figure 7. SRM State Space Model

information from observing the system responses. In traditional method, frequency spectrum can be viewed as system feature vector x. However, it is usually difficult to know each modal frequency exactly because the division of mode frequencies cannot be completed by signals accurately, especially for closed space frequencies or high frequencies decided by the complicated system structure and easily affected by noise. At the same time, the responses of a complex system have quite many close modal frequencies and high frequencies, and so it is very difficult to separate them from the time and frequency domains. Therefore, in many cases we have to give up the exact feature vectors instead with the approximate or new feature vectors. Naturally, we expect that the new features can reveal the characteristics of the original system. For example, the damping (or damping ratio) vector of each modal frequency is also an important feature in a vibration system. Therefore, the SRE can be expanded as:

$$\zeta = f(\lambda, \omega, \xi) = 1 \tag{19}$$

where, vector ξ is damping ratio of each modal frequency.

3.3 Extracting Damping Feature

The features of a damping vibration signal include its frequency and damping. **Figure 8(a)** shows a simulated SDOF damping vibration signal. The Fourier spectrum shown in **Figure 8(b)** is easy to know the frequency features of it. However, it is usually not easy to get the damping exactly because in general a damping vibration signal always includes many interference frequencies or noise. We can get the envelope curve as shown in **Figure 8(c)** by "Frequency Slice Wavelet Transform (FSWT)" time-frequency transform [10,11]. **Figure 8(d)** shows a result of time-frequency distribution of FSWT. The FSWT ensures that this distribution is located in a small localization time and frequency domains. Moreover, as

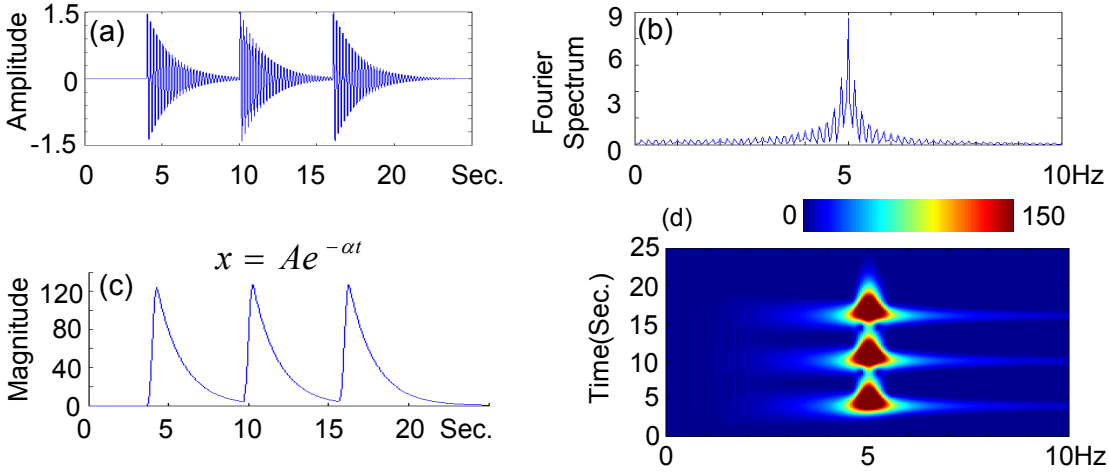

Figure 8 (a). SDOF damping vibration signal; **(b).** Fourier spectrum; **(c).** a FSWT slice curve; **(d).** 2D of FSWT time-frequency transform coefficients.

mentioned in Ref. [10,11], FSWT has many better properties and high performance against noise. Therefore, with the aid of FSWT, we can finish the feature extraction of vibration system. In order to simplify the computation of damping features and ensure their stabilities, we conduct a new damping method through the statistic methods as the following: We assume that the envelope curve is $x = Ae^{-\alpha t}$, when $t \in [0, T] \subset (0, +\infty)$. And let,

$$S(x^n) = \frac{1}{T}\int_0^T x^n dt \quad , n=0.5,\ 1,\ 2,\ 4. \tag{20}$$

It is obvious that $S(x^n)$ are easily computed from the time data x. Then the damping parameter α can be computed [3] by

$$\alpha = \frac{1}{T} f^{-1}\left(\frac{S(x^2)}{S^2(x)}\right), \text{ where } f(s) = \frac{s}{2}\frac{1+e^{-s}}{1-e^{-s}} \tag{21}$$

$$\alpha = 4\sqrt{S^2(\sqrt{x})S(x^2) - S^3(x)}\,/\left(S^2(\sqrt{x})\sqrt{S(x)}\right)/T \tag{22}$$

$$\alpha = 2\sqrt{S^2(x)S(x^4) - S^3(x^2)}\,/\left(S^2(x)\sqrt{S(x^2)}\right)/T \tag{23}$$

According to Eqs. (21)-(23), three statistic formulas are established to compute the modal transient damping. It is significant to note that $x = Ae^{-\alpha t}$ is an envelope curve of a damping vibration signal. The FSWT is used to get the envelope curve. Therefore, we can get the transient damping at any frequency and at any time by using FSWT. The modal damping function (*MDF*) is commonly denoted as,

$$\alpha = MDF\ (x) \tag{24}$$

Here, the *MDF* is obtained from one of the Eqs. (21)- (23) or any others, which can extract the parameter from a response frequency signal. Based on this idea, an important algorithm to extract the vibration feature vector is introduced, and it is applied to the vibration signal in detecting of a laboratory bridge monitoring system (LBMS) which was introduced in Ref. [3,4].

3.4 Feature Extract Algorithm

In a real bridge system, the system response may be stochastic. The system must make some responses when it is excited by environmental conditions such as cars, winds, earthquake, etc. Therefore, some trigger conditions ever exist. We call the time of a trigger condition as the Time Trigger Lines (TTLs). Now, we take a FSWT image as shown in **Figure 9** as an example to explain the feature extract algorithm. The FSWT clearly reveals the characteristics of the measured signal.

Featuring Algorithm

(1) Compute the FSWT expression for each sensor response, and denote it $W_i(t,\omega,\alpha)$, $i = 1,2,\ldots N_s$, where N_s is number of sensors.

(2) Take maximum of $|W_i(t,\omega,\kappa)|$, i.e. $|W|_M = \max_{t\geq 0,\omega\geq 0,i} |W_i(t,\omega,\kappa)|$ and record $(t_M, \omega_M, |W|_M)$ as a trigger condition.

(3) Define Frequency feature Sampling Line (FSL) and Time feature Sampling Line (TSL) Record M_f the number of all FSL and M_t the number of all TSL, and call small block as Feature Block (FB) (shown in **Figure 10**).

(4) Compute modal damping feature at each feature block as,

$$\alpha_{ipq} = MDF\left(\left|W_i(t,\omega,\kappa)\right|\right)\Big|_{(t,\omega)\in \mathrm{FB}_{pq}}, i = 1,2,...N_s, p = 1,2...M_f, q = 1,2...M_t$$

(5) Define: $V_i = (W_{\mathrm{M1}}, \alpha_{ipg})$ $i = 1,2,...N_s$, $p = 1,2...M_f$, $q = 1,2...M_t$, where,

$W_{ipq} = E\left(\left|W_i(t,\omega,\kappa)\right|\right)\Big|_{(t,\omega)\in \mathrm{FB}_{pq}}$, here $E(\cdot)$ means the average value, and call V_i the time-frequency feature (TFF) vectors of the system.

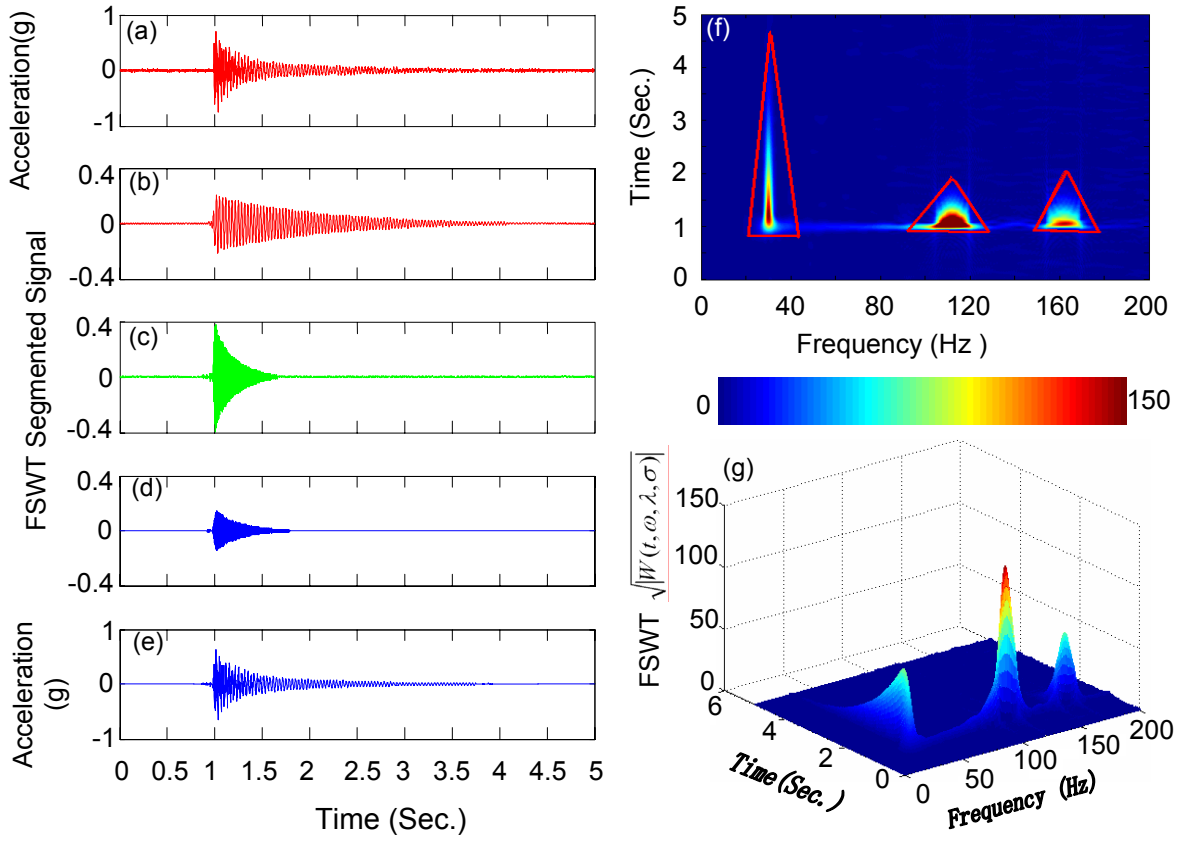

Figure 9. The left top **(a)** is original signal, there are three segmented signals **(b), (c)** and **(d)**, and the left bottom **(e)** is their synthesized signal. The right top **(f)** and **(g)** are amplitude 2D and 3D map of FSWT coefficients respectively for the original signal.

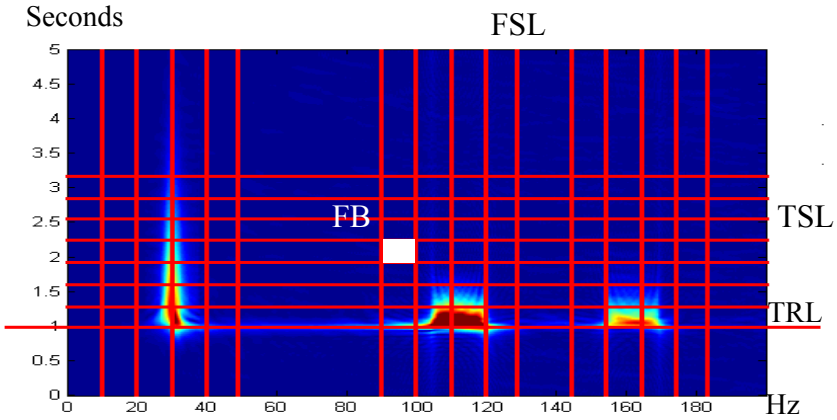

Figure 10. Feature Extracting Grids

Herein, let consider a real experiment from the LBMS [3,4]. Let $N_s = 11$, $M_f = 300$, $M_t = 3$, there are 1,200 features for each sensor, and acceleration sensor data has 9 impacts by hammer × 11 acceleration sensors ×10 times to test =990 groups. Therefore, there are 990×1,200 = 1.1M features, this is a huge numbers!! That is an obvious reason that the SRM must be a large size problem.

3.5 Overall Logics of SRM Method

Figures 11-14 show the overall logics of SRM method in this paper. The SRM provides several procedures for state assessment. The SRM has five main steps as follows:

(1) Computing signal feature,
(2) Solve feature model,
(3) Construct the state variable,
(4) Make the statistics of state variable,
(5) Assess the state changes between two test phases.

Figure 11 shows Step (1) of the SRM method: The SRM provides an important tool that can translate the signal space into the feature space of signal, where the FSWT is implemented to transform the time domain into the time-frequency domain. The FSWT has many better properties in contrast with the traditional wavelet. "**Featuring Algorithm"** is used to get the signal features. In this paper, although we mainly focus on the vibration signal, FSWT is available to many signals, especially for transient signals [10]. Naturally, one can use many tools to complete the feature extracting to build a feature database.

After getting features of signal, we use SRM Kernel Function to build a state equation. **Figure 12** shows Step (2): The SRM learn model is changed into a large-scale linear constraint problem. Because Eq. (14) in SRM is always ill-condition, over-determinate, and large-scale, therefore the SRM tool 1[11] is a necessary tool to solve Eq. (14).
After obtaining a solution of Eq. (14), we can use equation $\zeta = f(\lambda, x)$ to o describe the state condition of a system based on its response datum. **Figure 13** shows Step (3) and Step (4) of SRM method. A statistic distribution of state variable ζ can be completed easily. Step (1)-Step(4) are called the learning process of the SRM.

Figure 14 realizes the final aim of SRM, it includes the Step(4) and Step(5): If the learning work in a certain observing time is completed for a target system, the new observing data, called it test data set, will be obtained when the system changes as the time. The state description $\zeta = f(\lambda, x)$ is used to verify the change of the system. Therefore, we can get the similar distribution of the state variable ζ and some changes can be assessed by the SRM indices.

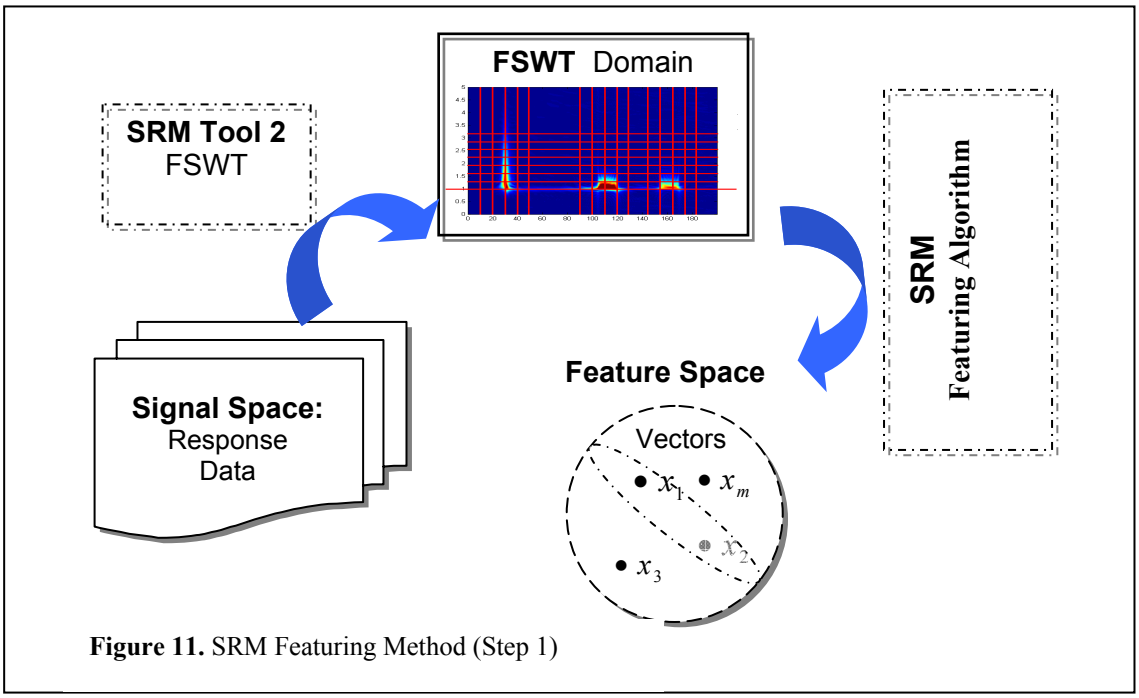

Figure 11. SRM Featuring Method (Step 1)

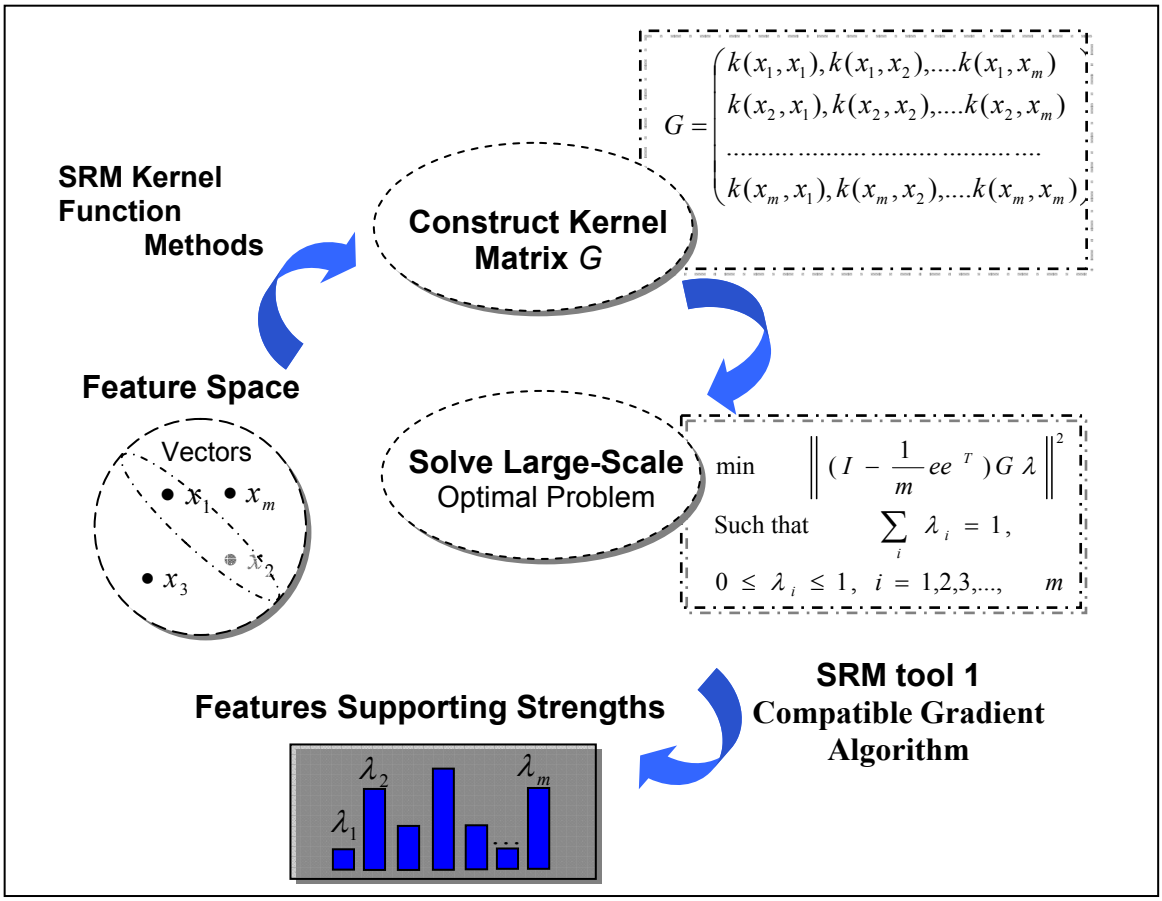

Figure 12. SRM Kernel Function Method (Step 2)

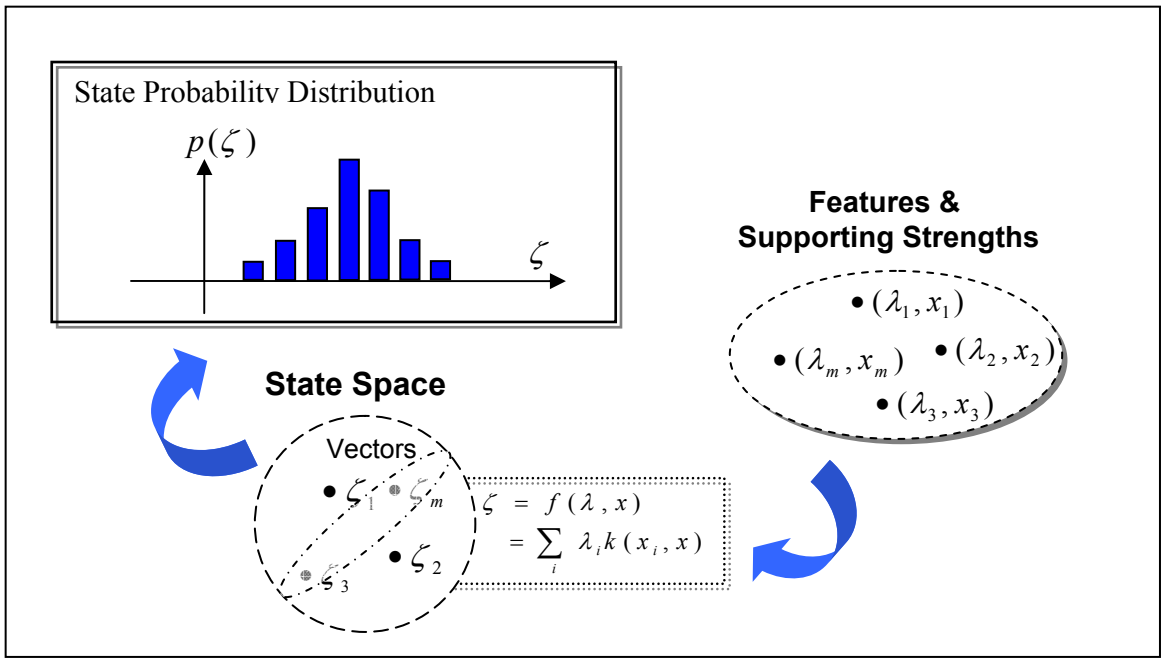

Figure 13. SRM State Computing & Statistic Method (Steps 3 & 4)

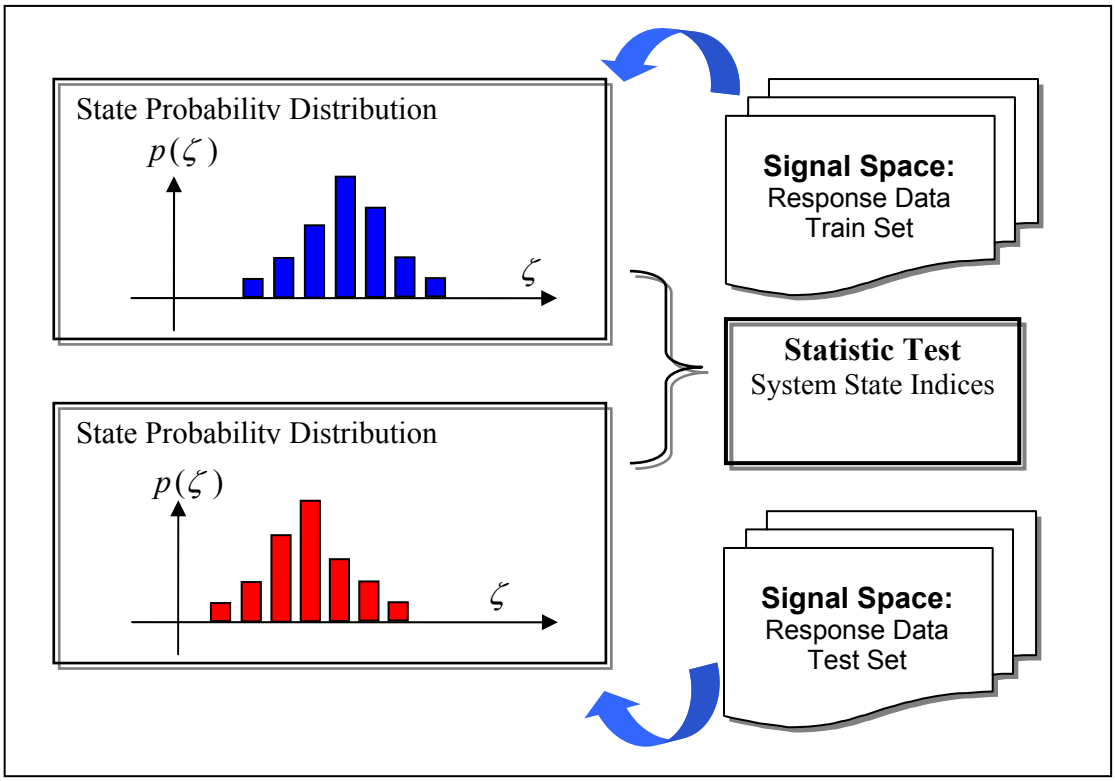

Figure 14. SRM State Comparing & Assessment (Steps 4 & 5)

4. Conclusions

This paper introduced the details of a newly proposed "State Representation Methodology (SRM)" and its application to bridge condition assessment based on the bridge monitoring data. The SRM is a novel tool that can provide some ideas and algorithms for data mining in the bridge monitoring system. The state of a system such as bridge structure could be obtained by a state variable ζ that calculate from a State Representation Equation (SRE). A Kernel function method which plays an important role in the Support Vector Machines (SVM) was applied to get solutions of the SRE. In the computation of the SRE, it needs to be changed into a Large-Scale Linear Constraint Problem (LSLCP). And a new time-frequency analysis tool, called Frequency Slice Wavelet Transform (FSWT), was able to powerfully reveal a change of the characteristics in vibration signal. Finally, an application example in the laboratory bridge monitoring system was presented so as to demonstrate how to apply the SRM to practical problems.

Main conclusions in this study are summarized as follows:

(1) SRM is a new idea for a non-parametric description of system state which described as the state variables.
(2) The state variables can be calculated by the state representation equation (SRE) for steady express the system state.
(3) SRM is an useful method for bridge condition assessment in structural health monitoring (SHM) system.

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