Moving Load Identification for STS Cranes Based on Hybrid Weighted Regularization Method

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Abstract. Moving force identification (MFI) is an important inverse problem in the field of structural health monitoring (SHM). However, reasonable signal features of moving forces are rarely considered in the existing MFI methods. Based on the redundant concatenated dictionary and weighted-norm regularization method, a hybrid method is proposed for MFI in this study. The redundant dictionary consists of both trigonometric functions and rectangular functions used for matching the harmonic and impact signal features of unknown moving forces. The weighted-norm regularization method is introduced for formulation of MFI equation, so that the signal features of moving forces can be accurately extracted. In order to assess the accuracy and the feasibility of the proposed method, an experiment based on Ship-to-Shore (STS) crane has been made and the results were discussed.

1. Introduction

At present, in the field of engineering practice, the bridge design specification has considered the moving load as an important component of the dynamic load of the bridge [1], and the moving load is also an important monitoring parameter for the health monitoring of bridge structures. Since the amplitude and position of moving load changes over time, it is difficult to obtain by direct measurement. So, the indirect acquisition of moving load, or called moving load identification technology has been paid widespread attention in the field of bridge engineering [2, 3]. Because the bridge is relatively simple in structure, most of the research methods simplify the bridge structure to simply supported beam and solve the problem by establishing its theoretical model [4, 5]. However, the structure of machinery is more complex than that of bridge structure, and it is difficult to establish its dynamic model through theoretical formula.

Take typical Ship-to-Shore (STS) crane whose self-weight is 1500 ton (fig.1) as example, its main beam is about 40 meters height from ground and nearly 200 meters long. A crane dolly moves on the main beam at 150 m/min maximum speed on it while can take as heavy as 100 ton cargos. Thus, the moving load for STS cranes is critical and is an important design basis for both structure and mechanism. Therefore, this paper considers the identification of moving load based on the establishment of a fine-tuned finite element model of STS container, which has a strong engineering significance.
2. Moving load identification based on over-complete dictionary and weighted L₁-norm regularization method

Unlike the existing BFM and Tikhonov regularization methods, the study of sparse regularization method in the MFI field seems not so much. Sparse regularization, in the mathematical inverse problem field, refers to a process of introducing additional sparse constraint information in order to solve an ill-posed problem. A sensible sparsity constraint is the $L_0$-norm, defined as the number of non-zero elements in estimated vector. Solving a $L_0$-norm regularized problem has been demonstrated to be non-deterministic polynomial hard (NP-hard) [6]. Therefore, $L_1$-norm constraint can be used to approximate the optimal $L_0$-norm via convex relaxation. Herein, $L_1$-norm constraint is defined as the sum of absolute values of elements in estimated vector. Obviously, the $L_1$-norm constraint is different from $L_2$-norm regularization method, in which the constraint is defined as $L_2$-norm of the estimated vector. Qiao et al. [7, 8] used the $L_1$-norm regularization method to identify both the impact force and harmonic force. Rezayat et al. [9] proposed a group-sparsity based method to identify both the unknown time history and unknown position of the dynamic force. The above methods are focused on the force reconstruction of fixed position. Bao et al. [10] used the $L_1$-norm regularization method for solving the distribution of moving heavy vehicle loads on cable-stayed bridges, however, only the time invariant forces are studied in this work. The biggest advantage of sparse regularization is for solving problem of feature extraction. As a convex optimization problem, the $L_1$-norm regularization is one of the most common used sparse regularization methods. However, the $L_1$-norm regularization always fairly penalizes all the components of unknown inputs. To overcome this draw, weighted $L_1$-norm regularization method is proposed in this study.

2.1. Over-complete dictionary method

As mentioned above, the research on signal characteristics of complex moving loads is less than the stability of solutions. Although the existing moving load identification method has a high stability of the solution, it is difficult to accurately estimate the main characteristics of the moving load. In this section, an over-complete dictionary containing trigonometric and rectangular functions will be used to match the signal characteristics of moving loads, and then the sparse programming method is used to extract the characteristics from the response of the STS crane. Since the literature [11] proposed the

![Figure 1. Typical working STS crane.](image)
concept for the first time in the 1990s, signal sparse representation has attracted widespread attention, and the theory of signal processing based on over-complete dictionary is very rich.

If for a set \( D = \{\phi_i, i = 1,2,3, \cdots, N\} \), whose elements \( \phi_i \) have the same nonzero length in the Hilbert space, then the set is called a dictionary whose elements are called atoms. The space formed by the elements of \( D \) satisfies \( (D) = H^d, d \leq N \). If \( d < N \), then the atom in this dictionary is not linearly independent, and this dictionary is called over-complete dictionary.

In the over-complete dictionary, the selection of atoms is an important part of sparse decomposition of signals. According to linear algebra, the following two points can be obtained:

1) It is extremely difficult to use a low-dimensional space to express a vector in a high-dimensional space unless the vector happens to fall entirely into this low-dimensional space;

2) For a given vector, its expression depends on the selected base vector. If there is a base vector that is along or opposite the direction of the vector, then there is only one nonzero element in the decomposition result of this vector.

For the moving load identification of STS Crane, the unknown load can be regarded as infinite dimension vector in Hilbert space. Therefore, it is preferable to use an infinite dimension dictionary. However, in practical calculations, this is not possible. It is hoped that a suitable finite dimensional space can be constructed to approximate the unknown load. In addition, according to the above second information, the expression of the sparse decomposition of the unknown load depends on the selection of the atoms. Therefore, in order to be able to express the unknown load completely and sparsely, when constructing the dictionary, the prior knowledge of the unknown load should be fully considered, so that the atoms can match the unknown characteristics of the unknown load as far as possible.

In fact, the spectra of STS crane’s moving load are very complex, it contains not only the ingredients that change slowly over time (which means these components close to static load), but also contains the local impact load. There are many basis functions that can be used for load identification, such as trigonometric functions, rectangular functions, orthogonal polynomial functions, spline functions, wavelet functions and so on. Among them, the trigonometric function has better frequency resolution, can characterize the component of periodic variation in moving load, and the rectangular function has better resolution of time domain, and can express the local impact component in moving load.

Thus, an over-complete dictionary containing both discrete trigonometric functions and discrete rectangular functions can be used to match the main characteristics of complex moving loads.

Assume that in the time period \([ t_1, t_2]\), the moving load moves on the STS crane. So that \( T = t_1 - t_2 \), then the trigonometric function can be expressed as:

\[
\phi_i^s = \frac{\sqrt{2\pi}}{T} \sin \left( \frac{\pi i}{T} (t - t_i) \right), \quad i = 1,2,3, \cdots, n_t
\]

\[
\phi_i^e = \begin{cases} 
\frac{\sqrt{T}}{T} & i = 0 \\
\frac{\sqrt{2\pi}}{T} \cos \left( \frac{\pi i}{T} (t - t_i) \right) & i = 1,2,3, \cdots, n_t
\end{cases}
\]

Assuming that the time interval \([t_1, t_2]\) is uniformly divided into \( n_r \) parts, the rectangular function is defined as follows:

\[
\phi_i^r = \begin{cases} 
\frac{\sqrt{n_r T}}{T} & t_1 + (i - 1) \frac{T}{n_t} \leq t < t_1 + i \frac{T}{n_t} i = 1,2,3, \cdots, n_t \\
0 & \text{otherwise}
\end{cases}
\]

All of the above base functions have the same length since the integration of squares of each base function from \( t_1 \) to \( t_2 \) is equal to 1. The number of base functions can be given by the following formula:

\[
n_t = n_r = [2 \times T \times f_r + 0.5]
\]
Where, $f_r$ is the maximum frequency of the unknown moving loads, and $n_r$ represents the round-off operation, according to Eq.1-4, a super complete dictionary $D = \{\phi, \phi \in \phi^s \cup \phi^c \cup \phi^r\}$ can be formed to express the moving load as:

$$y_1 = A_{11}\alpha$$

(5)

Where, $A_{11} = H_{11}\phi$. Eq.5 represents the case of single input and single output. For the case of multiple inputs and multiple outputs, it can be extended to:

$$\begin{bmatrix} y_1/\|y_1\| \\ y_2/\|y_2\| \\ \vdots \\ y_{ns}/\|y_{ns}\| \end{bmatrix} = \begin{bmatrix} A_{11}/\|y_1\| & A_{12}/\|y_1\| & \cdots & A_{1n_f}/\|y_1\| \\ A_{21}/\|y_1\| & A_{22}/\|y_1\| & \cdots & A_{2n_f}/\|y_2\| \\ \vdots & \vdots & \ddots & \vdots \\ A_{ns_1}/\|y_{ns_1}\| & A_{ns_2}/\|y_{ns_2}\| & \cdots & A_{ns_n_f}/\|y_{ns}\| \end{bmatrix} \begin{bmatrix} \alpha_1 \\ \alpha_2 \\ \vdots \\ \alpha_{n_f} \end{bmatrix}$$

(6)

Where, $y_1$ represents the response measured by the $i$ sensor. $\alpha_i$ is the coefficient vector of the $i$ moving load. $A_{ij}$ represents the transfer function from the $j$ moving load to the $i$ response. $n_s$ and $n_f$ are the number of sensors and moving loads, respectively. The value of the different sensors will be relatively large differences, so the response has been normalized.

2.2. Hybrid weighted $L_1$-norm regularization method

Through the above section we can see that the basic equation of moving load identification problem can be expressed as:

$$y = A\alpha$$

(7)

Where, $y$ is the structural response, $\alpha$ is the coefficient vector of the moving load, and $A$ is the transfer matrix. For this problem, the Tikhonov regularization method is a widely used method whose solution can be expressed by:

$$\alpha_{t\theta} = \arg \min_{\alpha} \{ \|A\alpha - y\|_2^2 + \lambda_{t\theta}\|\alpha\|_2 \}$$

(8)

Where, $\| \cdot \|_2$ represents the $L_2$ norm, $\lambda_{t\theta} \geq 0$ is the parameter of the Tikhonov regularization. However, since the solution of the Tikhonov regularization method is smooth, it can’t extract the main features of the signal. In order to obtain the sparse solution, we first think of the $L_0$ norm regularization method:

$$\alpha_{L0} = \arg \min_{\alpha} \{ \|A\alpha - y\|_2^2 + \lambda_{L0}\|\alpha\|_0 \}$$

(9)

Where, $\| \cdot \|_0$ represents the $L_0$ norm, which defined as the sum of the absolute values of all elements. However, the $L_0$ norm regularization problem is a difficult problem for non-deterministic polynomials, which is difficult to solve. Since the $L_1$ norm is the optimal convex approximation of the $L_0$ norm, it can be converted to solve the $L_1$ norm:

$$\alpha_{L1} = \arg \min_{\alpha} \{ \|A\alpha - y\|_2^2 + \lambda_{L1}\|\alpha\|_1 \}$$

(10)

Where, $\| \cdot \|_1$ represents the $L_1$ norm, which defined as the sum of the absolute values of all elements. $\lambda_{L1} \geq 0$ is the $L_1$ norm programming parameter. Equation 16 is the general $L_1$-norm regularization method, which takes indiscriminate penalty for all the components in the moving load, that is to say not
only the noise component is eliminated, but also the real component is penalized in the unknown load. Here, the weighted $L_1$-norm regularization method is used to improve the recognition accuracy of moving loads:

$$\alpha_{L_1} = \arg \min_{\alpha} \{ \| A\alpha - y \|^2_2 + \lambda L_1 \sum_i \omega_i |\alpha_i| \}$$  \hspace{1cm} (11)

Where, $\alpha_i$ and $\omega_i$ are the coefficients and weight coefficients of the $i$ force, respectively. For STS Crane, the static component occupies a large part of the composition of the moving load, so that the static part is not penalized here. Then the weight coefficient is defined here as:

$$\omega_i = \begin{cases} 0 & i \in Z_s \\ \frac{1}{\sqrt{|\alpha_i^{L_1}| + \epsilon_{\text{min}}}} & i \in Z_v \end{cases}$$  \hspace{1cm} (12)

Where, $\alpha_i^{L_1}$ is the value of the $i$ element calculated by the general $L_1$-norm programming method (Equation 8). $Z_s$ characterizes the static component, and $Z_v$ characterizes the dynamic component. $\epsilon_{\text{min}}$ is a positive trace, here set to $2.22 \times 10^{-16}$.

Since the $L_1$-norm regularization method is a convex problem, many optimization algorithms can be used. A fast-iterative threshold shrinkage algorithm proposed by the literature [12] is used to solve the weighted $L_1$-norm regularization method based on the idea of gradient descent.

3. Experiments and discussions

The finite element model of the STS container crane is used for numerical experiments. The sensor arrangement is shown in Fig.2 below and Fig.3 shows the scene of the experiment.

**Figure 2.** Sensor arrangement of numerical experiment
10% of the noise is added to the response in the numerical experiment, and the result is shown in Fig 4:

Through the above analysis, when the sensor position is 2, the identification accuracy at the No.2 sensor position is higher than that at the No.3 sensor position, and the maximum error is 8.9% when the noise level is 10%, which can be accepted by engineering practice. It is also found that when the load amplitude changes slowly, the error is relatively small, and when the load amplitude changes sharply, the error is large. The reason for this phenomenon is that the weighting $L_1$-norm regularization method is adopted, and the penalty of the dynamic component in the moving load is heavier. Therefore, when the dynamic component in the moving load is dominant, the recognition accuracy will decrease.

4. Conclusion
A hybrid approach to the identification of STS Crane’s moving loads based on the weighted $L_1$-norm regularization and the over-complete dictionary method. A super-complete dictionary with trigonometric and rectangular functions is used to match the main characteristics of unknown moving
loads, and the weighted norm regularization rule is used to extract the feature. Finally, a fast-iterative threshold shrinkage algorithm is used to solve the weighted norm regularization.

The numerical results show that the method can effectively identify the moving load, and the identification accuracy can be accepted by engineering practice. At the same time, the numerical experiment results also show that the prior knowledge of the moving load is taken into account when selecting the atoms in the over-complete dictionary, and the prior knowledge is also used to determine the weight of the weighted $L_1$-norm regularization method, so if the identified load does not follow the prior knowledge, the error will increase.

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