Structural Damage Detection by Integrating Independent Component Analysis and Support Vector Machine

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Abstract. Structural damage detection is very important for identifying and diagnosing the nature of the damage in an early stage so as to reduce catastrophic failures and prolong the service life of structures. In this paper, a novel approach is presented that integrates independent component analysis (ICA) and support vector machine (SVM). The procedure involves extracting independent components from measured sensor data through ICA and then using these signals as input data for a SVM classifier. The experiment presented employs the benchmark data from the University of British Columbia to examine the effectiveness of the method. Results showed that the accuracy of damage detection using the proposed method is significantly better than the approach by integrating ICA and ANN. Furthermore, the prediction output can be used to identify different types and levels of structure damages.

1 Introduction

Structural stiffness decreases due to aging, damages, and other harmful effects. These adverse changes lead to abnormal dynamic characteristics in natural frequencies and mode shapes. By instrumenting structures with a vibration sensor system, structural health monitoring (SHM) aims to provide reliable and economical approaches to monitor the performance of structural systems in an early stage so as to facilitate the decisions on structure maintenance, repair and rehabilitation [1, 11].

In the exciting field, researches have been studied on detect whether or not damage exists in a structure with varied approaches. A comprehensive literature review was made by Doebling and some successful methodologies were shown in his report [4, 5], such as employing changes in the natural frequencies and mode shapes, using measurements of flexibility, constructing statistical model, applying model-updating techniques and artificial neural network. From the view of datasets, these approaches used either time domain data or frequency domain data, measured from sensors in a structure. From the view of constructed models, they applied either physics-based models or data mining models (non physics-based models).

Pothisiri presents a physical damage detection model and its algorithm based on a global response of a structure [12]. This algorithm can locate one or more damaged members in a structure. However, it is not sufficient since it requires that the vicinity

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of the damage is known prior to the experiment and that the portion of the structure is easily accessible. As structures become larger and more complex, this method becomes unfeasible. Domain experts expect more efficient methods.

As the development of data mining techniques, it is possible to classify input signals or discovery patterns from large size of dataset without any prior background knowledge. In SHM, data mining techniques are used to identify the potential damage in a structure by using the variation of the dynamic response continually measured by sensors. Specifically, the first category problem is solved in two steps: 1) feature reduction from measured dynamic sensor data; 2) structure classification based on selected features. For the first step, ICA, mostly used in feature reduction from time series data, is a statistical and computational technique for revealing hidden factors that underlie sets of random variables, measurements, or signals. Recently, Zang [2] applied ICA to model damaged structures. Their results showed that ICA is a more robust method for feature selection and leads to more accurate classification. However, they didn't make deep and detailed analysis on the classification output. For the second step, both artificial neural network (ANN) and support vector machine (SVM) are active classifiers in this area. Especially, SVM, as a powerful kernel-based learning machine [9], has shown practical relevance for classification in various fields, such as object recognition [3], time-series prediction [10].

In this paper, we integrate ICA and SVM together to detect damages. By analyzing the independent components, we extract some features which include the information about the damage level and type. Next, the obtained components are input into SVM to classify structural damage. Our experiments, based on the benchmark data from the University of British Columbia, showed the prediction output can be used to identify different types and levels of structure damages.

2 Methodology

2.1 Feature Selection

ICA techniques provide statistical signal processing tools for optimal linear transformations in multivariate data and these methods are well-suited for feature extraction, noise reduction, density estimation and regression.

From a mathematical view, the ICA problem can be described as follows, each of h mixture signals $x_1(k)$, $x_2(k)$, …, $x_h(k)$ is a linear combination of q independent components $s_1(k)$, $s_2(k)$, …, $s_q(k)$, that is, X = AS where A is a mixing matrix. Now given X, we hope to compute A and S. Obviously, this is a difficult question since both A and S are unknown. Based on the following two statistical assumptions, ICA successfully gains the results: 1) the components are mutual independent; 2) each component observes nongaussian distribution.

The first one is a strong assumption about signals, even stronger than uncorrelated in PCA. It brings two advantages: we can compute the components in any order without considering the involvement of other components; uncorrelated is just partly independent, so PCA can be used as a pre-processing to whiten data and reduce the dimensionality, which greatly simplified the further processing work.

The second assumption is critical to separate signals. We see that gaussian signal looks like a nearly symmetric shape from all angles. If components observe gaussian distributions, by center limit theory, their linear combination of components should be more like gaussian, which becomes more difficult to separate. Hence, nongaussian is a necessary condition to extract components by detecting non-symmetric mixtures.

Specifically, with the second assumption, there are the following solution to solve the signal separation problems:

By $X = AS$, we have $S = A^{-1}X = WX$ (where $W = A^{-1}$). Hence, the task is to select an appropriate W which applied on X to maximize the nongaussianity of components. This can be done in an iteration procedure.

Different ICA algorithms measure nongaussianity by different methods. Some use Kurtosis function: $Kurt(y) = E[y^4] -3(E[y^2])^2$, which approaches 0 for a Gaussian random variable; some use negentropy: $negentropy(y) = H(y_{gauss}) - H(y)$ (H is entropy); some use approximations of negentropy for speeding up the computation: $J(y) = E[y^3]^2 / 12 + Kurt(y)^2 / 48$.

FastICA algorithm is applied in our application. The non-quadratic function $g(y) = \tanh(a_1 * y)$ is used to compute nongaussianity. The detailed algorithm steps are listed in [8].

2.2 Support Vector Machine Classifiers

It is known that SVM, proposed by Vapnik in 1995, has been achieving great success on classifying high-dimensional data. In the practice from many engineering fields, its accuracy is even better than neural networks.

Assuming data $D = \{(\vec{x}_i, y_i), i = 1...N\}$ with label $y_i \in \{-1, +1\}$, SVM transformed the attribute $\vec{x}$ into a higher-dimension attribute set $\vec{x}'$, and then separate data by a hyperplane in this hyper space. SVM assume the best linear classifier of the type $f(\vec{x}') = \vec{w}^T\vec{x}' + b = (w_1x_1' + w_2x_2' + ... + w_nx_n' + b)$ is the hyperplane in the middle of the gap (that is, maximize the margin between two classes of samples) shown in Fig.1.

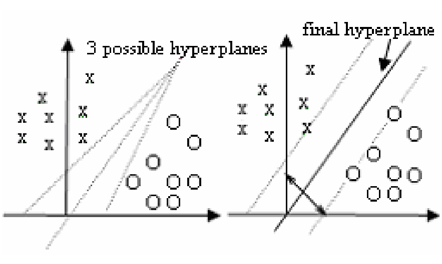

Fig. 1. The hyperplane for classification

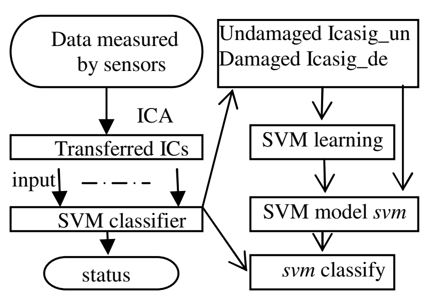

Fig. 2. Frame of integrating ICA and SVM

To seek the optimal **w** and **b** in $f(x) = (\mathbf{w}^T x + \mathbf{b})$ with maximal margin, SVM let the points closest to the separating hyperplane, $|\mathbf{w}^T x_i + \mathbf{b}| = 1$, called the support vectors, and for other points, $|\mathbf{w}^T x_i + \mathbf{b}| > 1$. Given f(x), the classification is obtained as +1 if f(x)>0, otherwise -1.

2.3 Frame Integrated ICA and SVM

The frame of integrating ICA and SVM is shown in Fig.2. The original time domain data measured by the sensors are first used as the input to ICA, and result in the independent component matrix. The matrix serves as the input attributes for SVM model.

3 Experiments

In this section, we will use both undamaged and damaged data as training data to construct a SVM model, and then apply it to test unseen data, exploring that if they are correctly recognized. In addition, the parameters of SVM were previously reported as an important influence over the classification accuracy. Consequently, we designed an experiment to see how they affect the performance in our case. Furthermore, we applied a trained SVM model on different types and levels of damaged data sets and analyzed if SVM model can distinguish them.

3.1 Data Sets

The data set, from the University of British Columbia, is a popular benchmark to testify the classification accuracies. They were developed by The IASC-ASCE SHM Task Group. The structure (Black and Ventura, 1998) is a 4-story, 2-bay by 2-bay steel-frame scale-model structure in the Earthquake Engineering Research Laboratory at the University of British Columbia. It has a 2.5 m $\times$ 2.5m plan and is 3.6m tall [7]. The detail Phrase II data can be reached by [6]. In our experiments, we mainly use 7 data sets in the ambient data from this benchmark, in which C01 data is undamaged data, C02-C07 data are different damaged data. For undamaged data, the structural status is '1' (undamaged), and for damaged data, the structural status is '-1' (damaged). The configuration key is attached in the last page, and the description is as following in [8].

Firstly, we input damaged and undamaged sensor data directly into SVM, though this is reasonable design, we could not obtain any suitable outputs since the computing could not converge at all. Hence, in the following experiments, we report our results by integrating ICA and SVM together for damage detection. C01 and one group data from C02 to C07, worked as input to ICA, whose size is 60000x15 (60000 examples with 15 features), then 10 independent components *Icasig_un* were computed and shown in Fig.3. (X axis presents the number of data and the unit is 10^4, Y axis presents the frequency).

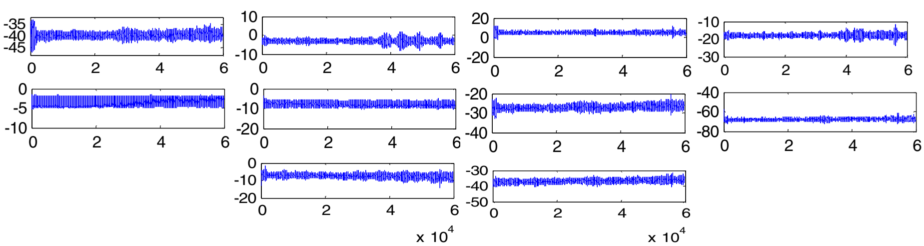

Fig. 3. Independent components of C01

3.2 Experimental Steps

(1)Experiment 1

For choosing the kernel function in SVM, the following experiments were done.

Experiment: Input data: undamaged data (*C01*), damaged data (*C02*)

Output data: structural status (undamaged 1 or damaged -1)

Step 1: Let undamage data ← *C01*; Let damaged data ← *C02* ;

Step 2: By using tanh as the non-gaussian function in FastICA algorithm, we compute the independent components from undamage data, the resulted ICs are denoted as *Icasig_un*;

Step 3: Select a number *t* as the type of different SVM kernel functions, initialize t←0.

Step 4: Randomly select *N* examples from *Icasig_un*, and 50% of them work as train set *Traind_de*, and the other 50% work as test set *Testd_de*.

Step 5: With the same settings on FastICA in all iterations at experiment 1, we compute the independent components from damaged data *C02*, the results are denoted as *Icasig_de*.

Step 6: Randomly select *N* examples from *Icasig_de*, 50% of them work as train set *Traind_de*, and the other 50% work as test set *Testd_de*.

Step 7: Traind ← combine *Traind_un* with *Traind_de*, build SVM model *svm*.

Step 8: Testd ← *Testd_de*. Use *svm* and *Testd* to predict the value for test data, if such value is beyond a scope s, the example will be classified as outlies, otherwise as undamage data.

Step 9: t ← t+1, repeat Step7 until t=4.

The results are shown in Table 1, in which, ‘trainCpusec’ means the cost CPU second in training data; ‘w’ is Norm of weight vector; ‘VCdim’ is estimated VC dimension of classifier; ‘testCpusec’ means the cost CPU second in classifying data. After consideration, t is assigned 0 in our experiments for training SVM model.

In addition, for trade-off between training error and margin, the corresponding parameter was changed from 0.5 to 2.5, but they did not affect the SVM model. We choose 1 as the trade-off value. The results showed that the liner kernel function and learning trade-off parameter 1 are optimal and will be used in the following experiments.

Table 1. Experiment for choosing Kernel function

t	0	1	2	3
meaning	linear function	polynomial	Radial basis	Sigmoid function
trainCpusec	0.08	0.02	0.05	0.02
$\lvert w\rvert$	0.435	0.078	2.777	1.000
VCdim	2.235	3.575	16.421	1.238
testCpusec	0	0	0.01	0
accuracy	0.999	0.618	0.992	1.000

(2) Experiment 2

In the experiment, ICA and SVM are combined to build a classification model by using undamaged data and damaged data. Then only damaged data is tested to see if they are classified correctly. The output data are structural status (undamaged 1 or damaged -1)

The classification accuracy is measured as Eq.1. Table 2 shows the experimental results, in which, each experiment use 40000 undamaged data C01 and 20000 damaged data from C02-C07 as train data, corresponding 20000 damaged data from C02-C07 as test data.

$$\text{accuracy} = \frac{\text{number of correct classification samples}}{\text{number of examples}} \quad \text{(Eq.1)}$$

Table 2. Prediction value by ICA and SVM with some C02-C07 as test data

	C02	C03	C04	C05	C06	C07
accuracy	0.986	0.979	0.983	0.992	0.962	0.996

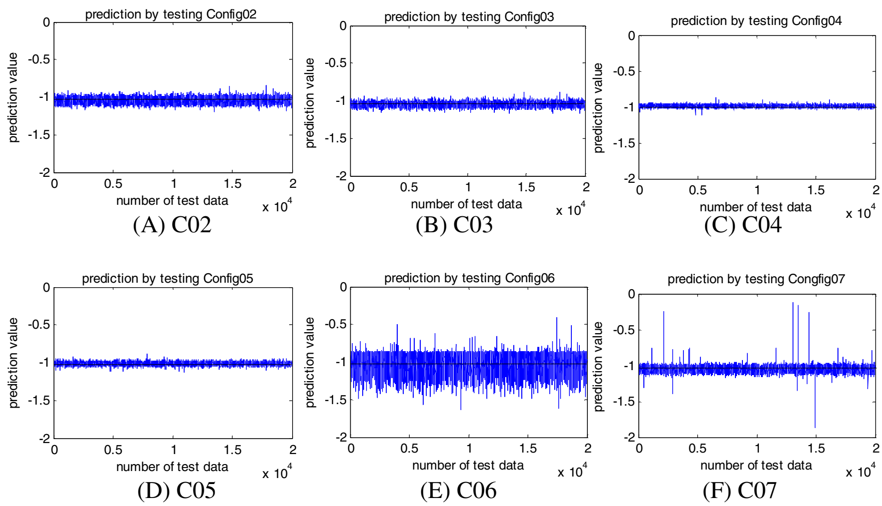

Fig. 4. Prediction by different data set

For looking for the difference damaged types, the prediction results are analyzed in details.

We observed that different types of damaged data result in the prediction value in different range. The prediction of C07 is nearest to -2 in negative direction and 0 positive direction, and has the biggest wave area. Among the damaged data from C02 to C05, and their wave areas are much smaller than C07. Therefore, C07 data might have biggest damaged level. It is proved by domain experts that all braced removed on all faces in C07 and should have the biggest damage level. In addition, from Fig.4A to Fig.4D, the wave area is reduced, especially in Fig.4C and Fig.4D, most of prediction values are bigger than -1, maybe C04 and C05 have similar damage level. According to the configuration key, Config04 removed braces on 1st and 4th floors in one bay on SE corner, and Config05 removed braces on 1st floor in one bay on SE corner. Therefore, the prediction value can show some information about damage level and damage type, and it help us to identify the different structural damage.

(3) Experiment 3

In the experiment, we aim to analyze the accuracy on classifying two classes of samples: undamaged and damaged data. Hence, the training and testing data are both sampled from two class data.

Table 3. Definitions of tp, fp,tn and fn

	True value=1	False value=-1
Prediction=1	tp	fp
Prediction=-1	tn	fn

Table 4. Accuracy using C01-C07 train and test

traind	C02	C03	C04	C05	C06	C07
1000	0.990	0.987	0.989	0.990	0.986	0.990
2000	0.993	0.990	0.990	0.992	0.989	0.992
4000	0.995	0.991	0.994	0.993	0.991	0.992
8000	0.996	0.994	0.995	0.992	0.992	0.993
10000	0.998	0.995	0.997	0.995	0.991	0.993
20000	0.998	0.995	0.997	0.996	0.990	0.994
40000	0.998	0.996	0.998	0.996	0.992	0.995

Since there are two classes of samples here, we measure the classification accuracy by Eq.2, in which, tp, fp,tn, fn are defined in Table 3. Table 4 shows the experimental results.

$$\text{accuracy} = \frac{\text{tp} + \text{fn}}{\text{tp} + \text{fp} + \text{tn} + \text{fn}} \qquad \text{(Eq.2)}$$

The above results are similar as the results in experiment 2. This showed that, there are obvious difference between the undamaged data and damaged data. Consequently, in experiment 1, the damaged data is classified as outliers; in experiment 2, such data is classified with correct class label. Hence, our results proved that by integrating ICA and SVM, we can extract the distinctive features for undamaged data and damaged data, and further effectively classify unseen data.

(4) Compare ICA-SVM and ICA-ANN

With the same experimental settings in experimental 3, we compared the performance achieved by integrating ICA and SVM with that achieved by integrating ICA and ANN [8]. Results in table 5 showed that ICA-SVM obtains better classification accuracy than ICA-ANN.

Table 5. Accuracy in ICA-ANN and ICA-SVM

data set	C01-C02	C01-C03	C01-C04	C01-C05	C01-C06	C01-C07
ICA+ANN	0.983	0.966	0.979	0.984	0.973	0.953
ICA+SVM	0.998	0.996	0.998	0.996	0.992	0.995

4 Conclusion

In this paper, we proposed an approach of integrating ICA and SVM for structure damage detection. In the first step, independent components are extracted from structure sensor data, which included signals about damage level and type. Next, the obtained components were input into SVM for structural damage classification. We evaluated our approach on the benchmark data from the University of British Columbia. The results from 3 experiments, all used both damaged data and undamaged data for training, showed that the accuracy of damage detection by the proposed method achieved significantly better accuracy than that obtained by use of ICA and ANN. Furthermore, the detailed analysis showed that we could identify different types and levels of damage from the prediction output, which are very useful conclusions for application in SHM.

In next step, we will continue to analyze the independent components for detecting the damage location and consequently support the repair decisions.

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