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Data-Driven Support Vector Machine with Optimization Techniques for Structural Health Monitoring and Damage Detection

Guoqing Gui*, Hong Pan**, Zhibin Lin***, Yonghua Li****, and Zhijun Yuan*****

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Abstract

Rapid detecting damages/defeats in the large-scale civil engineering structures, assessing their conditions and timely decision making are crucial to ensure their health and ultimately enhance the level of public safety. Advanced sensor network techniques recently allow collecting large amounts of data for structural health monitoring and damage detection, while how to effectively interpret these complex sensor data to technical information posts many challenges. This paper presents three optimization-algorithm based support vector machines for damage detection. The optimization algorithms, including grid-search, partial swarm optimization and genetic algorithm, are used to optimize the penalty parameters and Gaussian kernel function parameters. Two types of feature extraction methods in terms of time-series data are selected to capture effective damage characteristics. A benchmark experimental data with the 17 different scenarios in the literature were used for verifying the proposed data-driven methods. Numerical results revealed that all three optimized machine learning methods exhibited significantly improvement in sensitivity, accuracy and effectiveness over conventional methods. The genetic algorithm based SVM had a better prediction than other methods. Two different feature methods used in this study also demonstrated the appropriate features are crucial to improve the sensitivity in detecting damage and assessing structural health conditions. The findings of this study are expected to help engineers to process big data and effectively detect the damage/defects, and thus enable them to make timely decision for supporting civil infrastructure management practices.

Keywords: *optimization, data-driven modeling, support vector machine learning, structural health monitoring and damage detection*

1. Introduction

Large-scale civil engineering structures, including buildings, bridges, dams, and pipelines, are lifelines for economic and social need. Assessing their conditions and timely maintenance/mitigation are critical for structural health monitoring to ensure their health, extend their service life, and ultimately enhance the level of public safety (Sohn *et al*., 2001; Worden and Dulieu-Barton, 2004; Farrar and Worden, 2007; Lin *et al*., 2012; Lin *et al.*, 2013; Lin *et al.*, 2014; Kaveh *et al*., 2015). Integration of wireless sensor networks with Unmanned Aerial Systems (UAS) technology has recently demonstrated great potential for full-Spectrum Structural Health Monitoring (SHM) of the large-scale civil infrastructures (Watters *et al*., 2002; Worden *et al*., 2007; Huang *et al*., 2015; Ge *et al.*, 2016; Herrasti *et al*., 2016; Pan *et al*., 2016). These advanced sensor technologies are capable of collecting massive amounts of sensor data. The complexity and heterogeneity of the sensor data, however, post great challenges to data analysis for structural health monitoring and damage detection. Thus, it is in high demand in mining in-situ big data recorded from these large civil infrastructures and extracting sensitive features for damage detection.

Significant efforts on structural condition diagnostics and damage detection have been extensively undertaken (Magalhães *et al.*, 2012; Seyedpoor, 2012; Tibaduiza *et al.*, 2015; Cha and Buyukozturk, 2015). These studies could be mainly classified in two categories: a) physics-based approaches (Neerukatti *et al*., 2016; Pavlopoulou *et al*., 2016) and b) data-driven approaches (Liu *et al*., 2015; Tibaduiza *et al.*, 2015) and b) data-driven approaches (Liu *et al*., 2015; Tibaduiza *et al*., 2015). The first methods and techniques are based on physical-based vibratory characteristics of structural systems (Fahim *et al*., 2013), including

*Professor, School of Architecture and Civil Engineering, Jinggangshan University, Ji'an, Jiangxi 343009, China; School of Civil Engineering, Tongji University, Shanghai, 20092, China (E-mail: gqgui2011@163.com)

**PhD Student, School of Civil Engineering, Tongji University, Shanghai, 20092, China; School of Architecture and Civil Engineering, Jinggangshan University, Ji'an, Jiangxi 343009, Chin; Dept. of Civil and Environmental Engineering, North Dakota State University, Fargo, ND 58105, USA (E-mail: tjdxph@gmail.com)

***Assistant Professor, Dept. of Civil and Environmental Engineering, North Dakota State University, Fargo, ND 58105, USA (Corresponding Author, E-mail: zhibin.lin@ndsu.edu.)

****Associate Professor, School of Architecture and Civil Engineering Nanchang University, Nanchang, 300029, China (E-mail: lyhlez@163.com)

*****Assitant Professor, School of Architecture and Civil Engineering Nanchang University, Nanchang, 300029, China (E-mail: sandy_ncu@hotmail.com)

natural frequency, mode and curvature. The captured sensor data are usually integrated in the analytical models or simulations for calibration or interpretation to identify physical characteristics and assess the conditions of a structure. Although analytical models and simulation techniques are now well-established (Zou *et al*., 2000), rapidly and accurately interpreting large volumes of the sensor data still lag behind. This is particularly challenging when the physical models are not clear, such as a complex physical system or not sensitive physical-based characteristics. For example, the noise interference usually occurs in field measurements collection in sites, which may hinder the effectiveness of physical-based identification methods.

Differently, the data-driven approaches could extract sensitive features from sensor data to assess the structural conditions (Hou *et al*., 2000), regardless of the complexity of physical systems. By taking advantage of history sensor data, the data-driven models are robust to rapidly identify the key information from complex and heterogeneous sensor data, which may be no longer valid for the physics-based approaches. Among the data-driven approaches, the machine learning techniques have been raising increasing attentions to data mining for SHM applications. There are a variety of machine learning techniques, including Bayesian networks (Masri *et al.*, 2000), artificial neutral networks (Zang and Imregun, 2001) and Support Vector Machines (SVM) (Oh and Sohn, 2009).

The SVM algorithms have been widely accepted as effective tools for extracting features and detecting damages (Worden and Lane, 2001; Bornn *et al.*, 2009; Yeesock *et al*., 2013).This method has high accuracy and sensitivity for damage identification (Chong *et al*., 2014). Dushyanth and Suma (2016) developed a new multilevel SVM and stated that the proposed SVM method required much less training data as compared to others. Some researcher continued this work. Ghiasi and Torkzadeh (2016) further developed the multilevel SVM from the initial study (Chong *et al*., 2014) through new kernel function based SVM. Their results confirmed that Littlewood–Paley wavelet kernel function could generate a higher accuracy in classification than other conventional kernel functions. Note that the accuracy of the SVMs for damage classification highly depends on the feature data and the proper parameters of the algorithm, such as the penalty coefficient, C, and kernel function parameter, γ. These parameters are usually unknown beforehand for a given problem, while it is still a big challenge to select proper ones.

Therefore, this study is to investigate the feasibility of using the data-drive support vector machines integrated with optimization techniques for enhanced feature extraction and parameter optimization in SHM and damage detection. Two types of feature extraction methods, including parameters of the autoregressive model and the residual errors of the statistical parameters, were selected. Three optimization techniques, grid search method, particle swarm optimization and genetic algorithm, were used to effectively determine the parameters in the SVM. A case study in the literature was used to verify the concept and demonstrate the effectiveness and sensitivity of enhanced SVM for damage detection.

2. Date Process and Features for Damage Detection

2.1 Data Mining in SHM applications

Data mining in the SHM is crucial to gain key information for assessing structural health and identifying potential damages/defects. The statistical pattern recognition paradigm in SHM applications has recently been proposed (Farrar and Worden, 2013), as shown in the flow chart in Fig. 1. The data mining process is classified into four steps: (a) operational evaluation; (b) data acquisition; (c) feature extraction; and (d) statistical model development for feature classification.

The advanced sensor network systems using the wireless passive networks with UAS enable collecting massive amounts of data for SHM and damage detection (Ge *et al*., 2016; Pan *et al.*, 2016). As stated early, the physics-based and data-driven methods (particularly machine learning) are two approaches for conditional assessment and damage detection. The framework, illustrated in Fig. 1, displays the workflow from the big sensor data acquired from wireless sensor systems to sensitive feature extraction. Consider that data type is time series, the autoregressive (AR) model is thus selected to extract damage-sensitive features from time-series data (Yao and Pakzad, 2012; Ying *et al*., 2013). SVM learning algorithms are specifically designed for classification between damage and undamaged cases, where the Radial Basis Function (RBF) kernel are herein chosen as the kernel function, as detailed in the following sections.

2.2 Features Extraction for Damage Detection

Feature extraction is to convert existing features into a lower dimensional space, where reduced features will avoid the

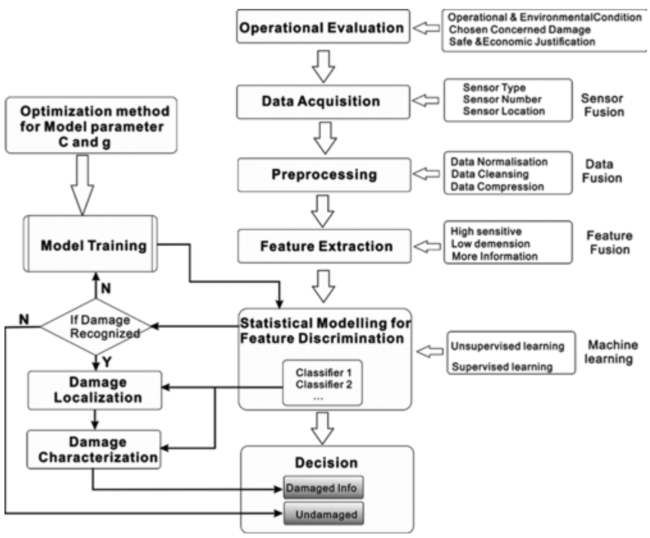


Fig. 1. Data Mining Process for SHM and Damage Detection (revised after Ying *et al*., 2013)

redundancy due to high-dimensional data (Widodo and Yang, 2007). The model has been widely accepted for time-series analysis and thus we selected this model, which has p parameters by the form:

$$x_i = \sum_{j=1}^{p} \phi_j x(i-j) + e_i \tag{1}$$

where x_i is the measured discrete signal, i is the time step, and e_i is an error. ϕ_j is unknown AR parameters. The AR parameters can be solved using Least squares or the Yule-Walker equations (Gersch, 1970). AR parameter has an inner-relationship with structural physical properties, and thus it is useful as a damage-sensitive feature (Yao and Pakzad, 2012). Its Residual Error (RE) is defined as:

$$e_i = x_i - \hat{x}_l \tag{2}$$

where $\hat{x}_l$ is the predicted signal value as compared to the measured signal x_i. The residual errors could include nonlinear effects and be derived from normal condition (Figueiredo *et al.*, 2009).

Previous studies (Boldt *et al.*, 2013; Figueiredo *et al.*, 2009; Sharma *et al.*, 2016) demonstrated that the parameter *RE*, as the statistical feature of the AR model, could exhibit high sensitivity as damage features. Thus, a total of sixteen statistical features from the residual errors were summarized from the literature (Boldt *et al.*, 2013; Figueiredo *et al.*, 2009; Sharma *et al.*, 2016), as listed in Table 1. These statistical features include the maximum of the residual errors vector (abbreviated as Maximum); minimum of the residual errors vector (abbreviated as Minimum); mean value (abbreviated as Mean); the magnitude of maximum minus minimum (abbreviated as Maximum-Minimum) and Mean of absolute value. Also, the standard deviation, skewness; Kurtosis, and Root Mean Square (RMS) are considered. Form factor; Crest factor; Kurtosis factor; Pulse factor; Margin factor; 99.73% confidence intervals upper control number (Upper control limit) and 99.73% confidence intervals lower control number (Lower control limit) are shown in Table 1 as well.

The order of AR model could influence the accuracy and the integrity of the model. To determine the optimized order in the model, the Akaike Information Criterion (AIC) method is used (Figueiredo *et al.*, 2011) by the form:

$$AIC(p) = N \cdot \ln \sigma_p^2 + 2p \tag{3}$$

where, p is the determination of the model order; N is the samples number; and σ_p^2 is the prediction variance of p order model. The first term at the right side of Eq. (3) represents the fitness of the model, while the second term relates to the order of the model. Note that it is a trade-off between the accuracy of the model and

Table 1. Definition of Statistical Feature

Feature	Formulations	Feature	Formulations
Maximum	$RE_1 = \max(e_i)$	RMS	$RE_9 = rms = \sqrt{\frac{1}{N}\sum_{j=1}^{N} e_i^2}$
Minimum	$RE_2 = \min(e_i)$	Form factor	$RE_{10} = \frac{rms}{\frac{1}{N}\sum_{j=1}^{N} \lvert e_i \rvert}$
Mean	$RE_3 = \mu = \frac{1}{N}\sum_{j=1}^{N} e_i$	Crest factor	$RE_{11} = \frac{\max(e_i) - \min(e_i)}{rms}$
Maximum-Minimum	$RE_4 = \max(e_i) - \min(e_i)$	Kurtosis factor	$RE_{12} = \frac{\sum_{i=1}^{N} e_i^4}{\sqrt{\sum_{i=1}^{N} e_i^2}}$
Mean of absolute value	$RE_5 = \frac{1}{N}\sum_{j=1}^{N} \lvert e_i \rvert$	Pulse factor	$RE_{13} = \frac{\max(e_i) - \min(e_i)}{\frac{1}{N}\sum_{i=1}^{N} \lvert e_i \rvert}$
Standard deviation	$RE_6 = \sigma = \sqrt{\frac{\sum_{j=1}^{N}(e_i - \bar{e}_i)}{N}}$	Margin factor	$RE_{14} = \frac{\max(e_i) - \min(e_i)}{\left[\frac{1}{N}\sum_{j=1}^{N} \sqrt{\lvert e_i \rvert}\right]^2}$
Skewness	$RE_7 = \sqrt{\frac{1}{6N}\sum_{j=1}^{N}\left(\frac{e_i - \mu}{\sigma}\right)^3}$	Upper control limit	$RE_{15} = UCL = \mu + 3\frac{\sigma}{\sqrt{n}}$
Kurtosis	$RE_8 = \sqrt{\frac{N}{24}}\left[\frac{1}{N}\sum_{j=1}^{N} - 3\right]$	Lower control limit	$RE_{16} = LCL = \mu - 3\frac{\sigma}{\sqrt{n}}$

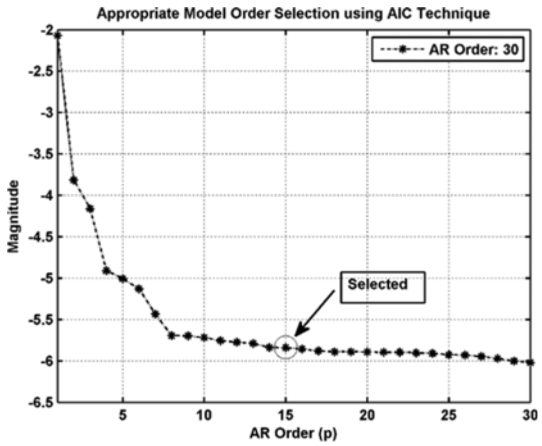


Fig. 2. AIC Values Over the AR Order

the model complexity. Fig. 2 shows the AIC values predicted by Eq. (3) in terms of a function of the order of AR models and p = 15 is selected based on the coverage of AIC value and the number of statistical parameters.

3. Support Vector Machine and Its Optimization Techniques

3.1 Support Vector Machine

The SVM is an effective machine learning technique for data classification (Suykens and Vandewalle, 1999). As clearly illustrated in Fig. 3, the SVM is to construct a hyperplane that separates two different classes of data samples based on available acquired data (i.e., training data) and to maximize the "margin" from the hyperplane to the closest data points in either class. By applying Kernel function (e.g., linear, polynomial or Gaussian radial basis function) as the inner product of functions mapping the data to a high dimensional feature space, the SVM could also be applied in a case of non-linear classification. It is not necessary to explicitly evaluate mapping in the feature space (Furey *et al.*, 2000).

The whole process of the SVM is illustrated in Fig. 4. Note that it is impossible the given data always be separable and thus

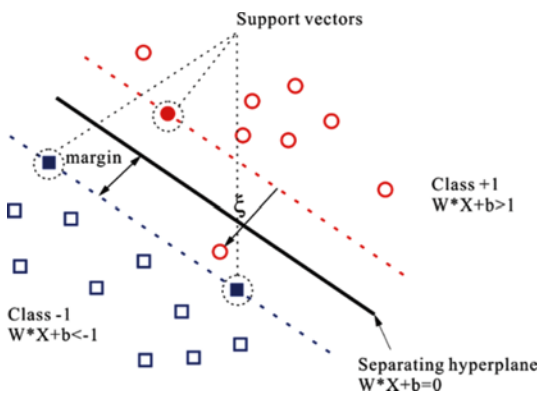


Fig. 3. SVM: Optimal Hyperplane and Maximum of Margin Hyperplanes

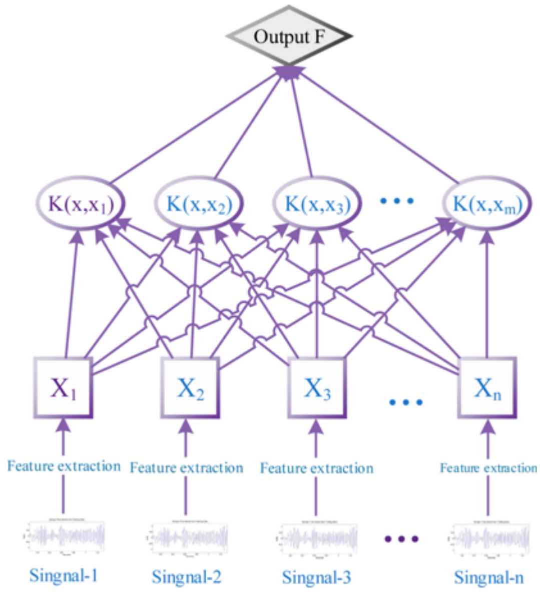


Fig. 4. Flowchart of the SVM Algorithm

it is more reasonable to filter few outlier data points. To effectively operate that, soft margin of the SVM, including the slack variable ξ_i and the error penalty C, are defined by:

$$\text{Margin} = \frac{2}{\|w\|^2} \tag{4}$$

and the optimization of the solution will be:

$$\min\left(\frac{1}{2}\|w\|^2 + C\sum_{i=1}^{N}\xi_i\right) \tag{5a}$$

$$\text{subject to } y_{i(w,X)} + b \geq 1 - \xi_i, \;\; \xi_i \geq 0 \tag{5b}$$

where w and b are the vector and scalar that are used to define the position of the hyperplane, respectively. ξ_i is a distance measured between the hyperplane that stays in the wrong side of the hyperplane. By using Lagrange multipliers algorithm to solve the dual optimization problem as shown in Eqs. (5a) and (5b), the non-linear decision function will yield:

$$f(x) = sign\left(\sum_{i=1}^{N}\alpha_i y_i K(x, x_i) + b\right) \tag{6}$$

where

$$K(x, x_i) = \exp(-\gamma\|x_i - x_j\|^2), \qquad \gamma > 0$$

where the $K(x, x_i)$ is the Radial Basis Function (RBF) and it is defined as the kernel function. By using this kernel function, it can analyze higher dimensional data.

3.2 Optimization Techniques

As stated early, selecting suitable penalty coefficient and kernel function parameter for the SVMs could enhance their accuracy for damage classification. Three representative optimization techniques are selected to optimize the parameters in the SVM: a) Grid-search techniques (GS); b) Particle Swarm Optimization (PSO); and c) Genetic Algorithm (GA), which are addressed in detail below. Note that these three widely accepted approaches are selected for

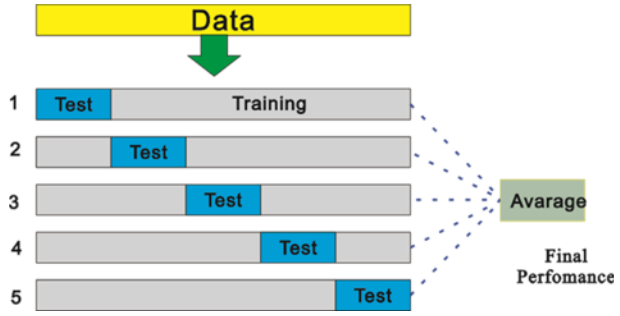


Fig. 5. Cross-validation Technique

simplicity to demonstrate the proposed concept, although there are many optimization techniques in the literature and they could be used to gain more information from optimization viewpoints.

To effectively estimate the accuracy of the models, the Cross-validation (CV) procedure is used, which is also to prevent the overfitting problem. Fig. 5 shows the process of the CV technique (Bisgin *et al.*, 2011). Firstly, the training data are randomly divided into the V subset in equal size. The second step is to use the V-1 subsets to train a model and then test the remaining subsets. As such, the final average validation of the measured performance is generated.

The V subset is usually selected at random. As a result, some subsets may have apparently different distributions to others. Therefore, it is important to select the subsets that have roughly identical features to others. The size of subset is another challenge during the CV process. Thus, there is a trade-off between true error estimator and the variance of the estimator, as the number of subsets increase. The bigger number the subset has, the smaller true error rate and the bigger variance will be. We empirically select three subsets herein.

3.2.1 GS-SVM

The parameters, C and γ, are selected using the grid-search method. The optimized parameters are chosen from various pairs of (C,γ). As clearly illustrated in Fig. 6, the main idea of the GS method in the SVM is to list all of the possible parameters pairs (C,γ) using an orthogonal grid point matrix and then calculate the potential fitness values of this point. With such, the maximum or minimum fitness value is selected from all data pool. The GS method is simple and straightforward, but requires more computing time as compared to other methods. However, there are several advantages by using this simple approach (Hsu *et al.*, 2010). Firstly, it is safe to run an exhaustive parameter search. Secondly, there are only two parameters in this problem, so the computing time will not increase significantly. Last, the GS technique has independent parameters. As a result, it is easily parallelized, which is usually difficult to achieve if using other advanced methods.

Specifically, to effectively yield better results, a coarse grid is firstly used as initial data sieving, with which one can find a better region on the grid. Further finer grid search helps to determine the final results.

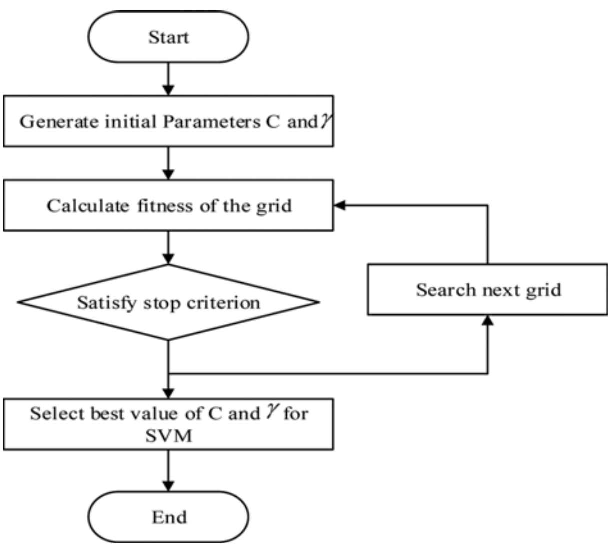


Fig. 6. Flowchart of the GS-SVM Algorithm

3.2.2 PSO-SVM

The PSO was first introduced by Kennedy and Eberhart (Kennedy and Eberhart, 1995). The PSO algorithm comes from the inspiration of the behavior of swarms such as schools of fish, flocks of birds that are able to adapt to the changes in their environment and find food or avoid predators by sharing information. The PSO is starting with a set of randomly generated solutions, and with the information in the design space shared by all of other members of the swarm, ends with a global optimum solution over a number of iterations. The PSO algorithm consists of three main steps: a) generating particles positions and velocities; b) updating velocity; and c) updating final position. The initial swarm is randomly generated using the upper and lower bounds of the design variables. Then the position of partials under each iteration is updated to:

$$X^j_{i+1} = X^j_i + V^j_{i+1}\Delta t \tag{7}$$

The PSO-SVM method is herein to optimize the accuracy of the SVM classifiers. As schematically illustrated in Fig. 7 for the main

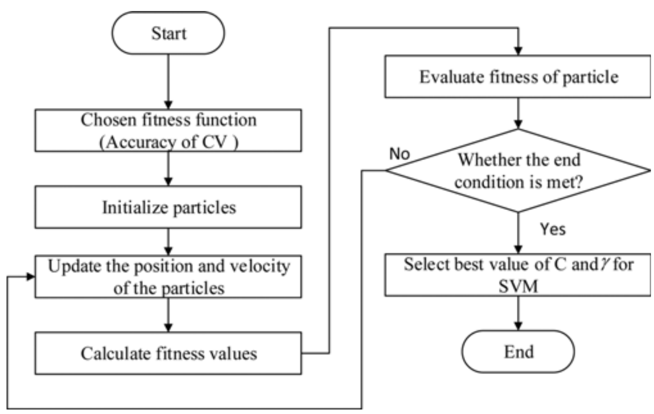


Fig. 7. Flowchart of the PSO-SVM Algorithm

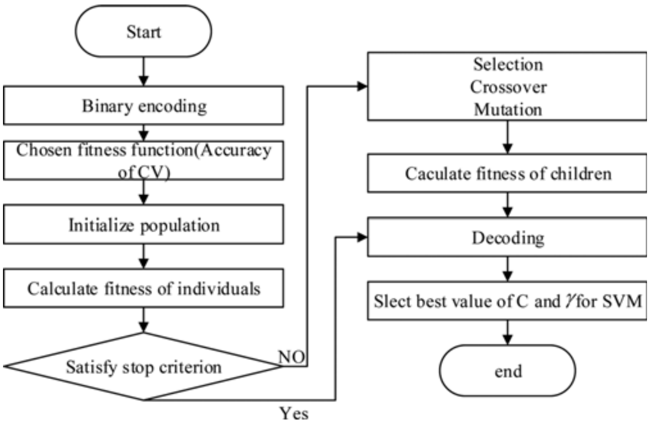
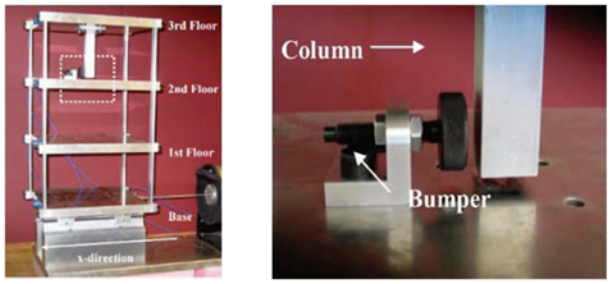


Fig. 8 Flowchart of the GA-SVM Algorithm



(a) (b)

Fig. 9. Three-story Frame Structure (Figueiredo *et al*., 2009): (a) Three-story Building Structure and Shaker, (b) Adjustable Bumper and Column

process of the PSO-SVM, this method is to use the training data to automatically select the best SVM model in terms of determining the best error penalty C and γ (Huang and Dun, 2008; Melgani and Bazi, 2008). Classification accuracy is a criteria to define the fitness function in the SVM (Huang and Dun, 2008).

3.2.3 GA-SVM

The GA is an adaptive heuristic search algorithm based on the concept of the natural evolution. The GA was developed by Holland (Holland and ARbor, 1975) through creating a new artificial system on the basis of natural adapting behavior in environment and searching optimized solutions using a random search (Yan and Lin, 2016; Yan *et al*., 2016). By taking advantage of using the historical information, the GAs will direct the search into a better region, through a competition among the individual results. The competition between the previous generations includes selection, crossover and mutation toward the fittest individuals. The GA yields rapid, robust, and accurate solutions due to the integration of direction and adaptiveness to change in the operation process. The critical information from the previous solutions is inherited to the following ones and thus leads to rapid and optimal results.

Flowchart of the GA-SVM algorithm is plotted in Fig. 8. Clearly, in the GA-SVM method, the GA is to select the proper parameters for optimizing C and γ for the SVM classification (Li and Zhang, 2009). The SVM-based classifiers are effective for constructing the fitness function, while the use of the CV technique can further tailor the fitness of each fold. As a result, the GA-SVM method could be effective tools with high accuracy to predict the testing data.

4. Case Study

4.1 Prototype Structures and Data-driven Studies

As shown in Fig. 9, the case is a small-scale three-story frame aluminum structure (Figueiredo *et al.*, 2009). Nonlinear damage was intentionally introduced by adjusting the gap between the bumper and the column as shown in Fig. 9(b). Note that although

Table 2. Test matrix and All of the Structural State Conditions

Label	State Condition	Description
Undamaged states (# 1 to 9)		
State#1	Undamaged	Baseline condition
State#2	Undamaged	Added mass (1.2 kg) at the base
State#3	Undamaged	Added mass (1.2 kg) on the 1st floor
State#4	Undamaged	States 4–9: 87.5%stiffnessreductionat Various positions to simulate temperature impact (more detail in the reference)
State#5	Undamaged	
State#6	Undamaged	
State#7	Undamaged	
State#8	Undamaged	
State#9	Undamaged	
Damaged states (# 10 to 17)		
State#10	Damaged	Gap (0.20 mm)
State#11	Damaged	Gap (0.15 mm)
State#12	Damaged	Gap (0.13 mm)
State#13	Damaged	Gap (0.10 mm)
State#14	Damaged	Gap (0.05 mm)
State#15	Damaged	Gap (0.20 mm) and mass (1.2 kg) at the base
State#16	Damaged	Gap (0.20 mm) and mass (1.2 kg) on the 1st floor
State#17	Damaged	Gap (0.10 mm) and mass (1.2 kg) on the 1st floor
State#10	Damaged	Gap (0.20 mm)

the developed data-driven machine learning methods presented in Section 3 were herein verified using a building found in the literature, they are applicable to damage detection of other civil, mechanical and aerospace systems with minimized limitations, which is the best feature in data-driven methods over conventional physical-based methods.

Table 2 shows the designed 17 different scenarios. Each scenarios has 10 times testing and each floor has been installed with an acceleration sensor. Different damage features about this structure have been studied including: statistical moments, autoregressive model, model parameters, and holder exponent (Figueiredo *et al*., 2009). The damage was introduced by narrowing the gap between the bumper and the column. The contact of the bumper and the column increased the stiffness of the top floor when they impacted each other, which also increased the high frequency parts of the damage scenarios. The parameters AR and

Table 3. Comparison of the Proposed Study with Existing Ones in the Literature

	Methods	Feature	Prediction Error
Existing studies	Auto-associative neural network*	AR Parameter	4.30%
	Factor analysis*		4.20%
	Mahalanobis squared distance*		4.00%
	Singular value decomposition*		4.60%
	One-class **SVM****		3.36%
	Support vector data description**		3.44%
	Kernel principal component analysis**		2.72%
	Greedy kernel principal component analysis**		2.64%
Proposed study	PSO+**SVM**	AR Parameter	2.35%
	GA+**SVM**		2.35%
	GS+**SVM**		1.18%
	PSO+**SVM**	AR Residual	0.00%
	GA+**SVM**		0.00%
	GS+**SVM**		0.00%

Note: *: Figueiredo *et al*., 2011; **: Santos *et al*., 2016

RE have been selected as damage features. As stated in Section 2, both parameters have a good sensitivity to such nonlinear property.

4.2 Calibration of the Proposed Methods

To calibrate the effectiveness of the proposed methods, particularly verify the optimization techniques used in the SVM, several existing studies in the literature (Figueiredo *et al*., 2011; Santos *et al*., 2016) that used the same benchmark as stated in Section 4.1 are used for a comparison, as listed in Table 3. These existing methods include auto-associative neural network, singular value decomposition and one-class SVM. Clearly, different methods exhibit somehow different levels in accuracy, ranging from five to three percent deviation for feature extraction and damage detection prediction. For example, Auto-associative neural network has an accuracy of 4.3 percent in prediction, while the one-class SVM reaches up to 3.36 percent deviation to true solutions. As a comparison, the proposed SVM with optimization techniques (PSO, GA and GS) could yield a better prediction when using AR features within 2.5 percent, which confirms that the use of optimization could help selection of the parameters in the damage detection. Moreover, three optimized based SVM could further increase accuracy to one hundred percent when using the RE as damage features. It can be envisioned that the proposed machine learning with optimization techniques will be more robust when under those complex data.

5. Results and Discussions

5.1 Feature Sensitivity and Amplitude

To better understand performance of the proposed machine learning techniques, selection of effective and sensitive damage features are in high demand, since a perfect damage sensitive feature is theoretically sensitive and robust to all kind of damages even under high variations and other interference. The 3rd floor's senor data have been selected as the benchmark to demonstrate our concept. A total of twenty-one features are selected from fifteen cases of the AR_i (i = 1, 2,..., 15) and sixteen of the RE_i(i = 1, 2, ..., 16). Each group is illustrated in Figs. 10(a) and 10(b) by the box-and-whisker diagram.

Clearly, the RE_i reaches up the bigger difference in magnitude between each parameter than that of the AR_i parameter, suggesting that the RE has more sensitivity to detecting damages than the AE. Moreover, the RE_i has more outlier than the AR_i parameter, while the skews of RE_i is the bigger as well, and thus the RE_i is more divergent and irregular than the AR parameter, which further confirmed that the RE is more sensitive as the damage feature than the AE.

Figures 11 and 12 are plotted for both features AR and RE to demonstrate the level/amplitude of different feature parameters for undamaged or damage states. The AR_1 and AR_7 are found as the best sensitive features among the AR parameters to distinguish between undamaged and damaged states, while the RE_1 and RE_3 are the best ones in the RE parameters. As clearly illustrated in Figs. 11(a) and 11(b), two plots have different

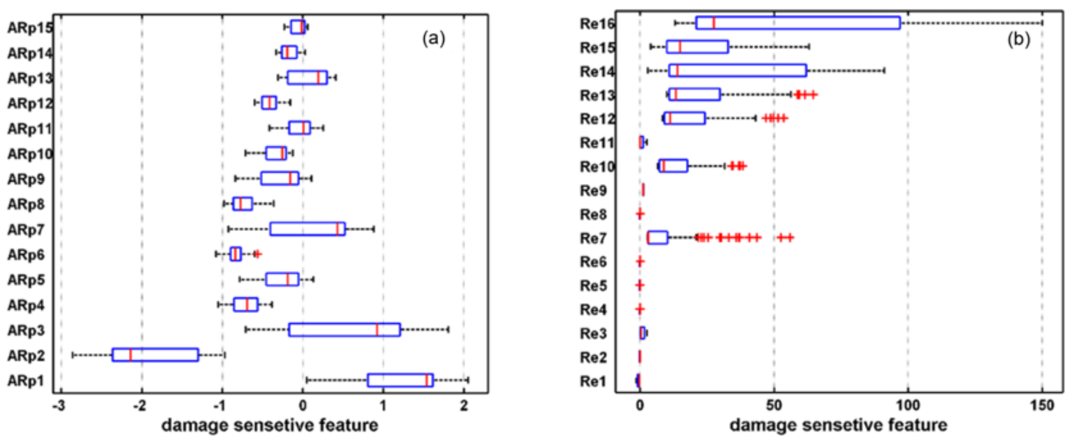


Fig. 10. Box-and-whisker Diagram of Damage Sensitive Features: (a) AR Type, (b) RE Type

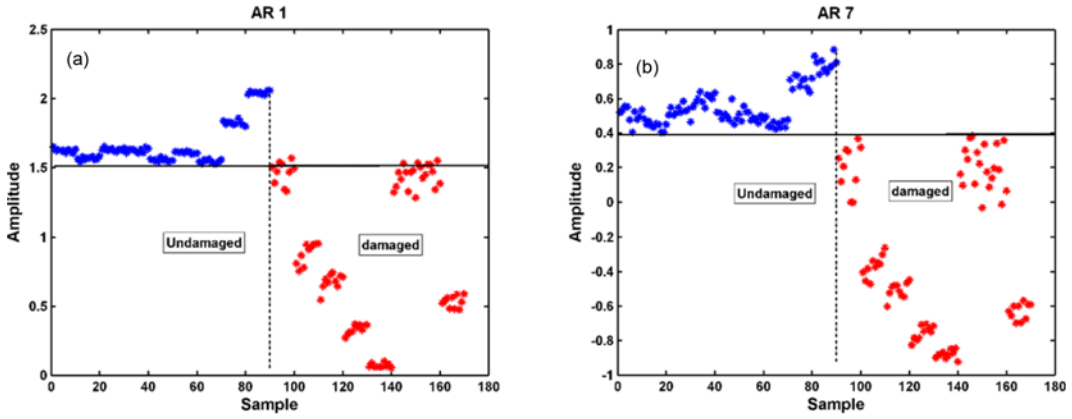


Fig. 11. Amplitudes from Damaged and Undamaged Condition: (a) AR_1, (b) AR_7

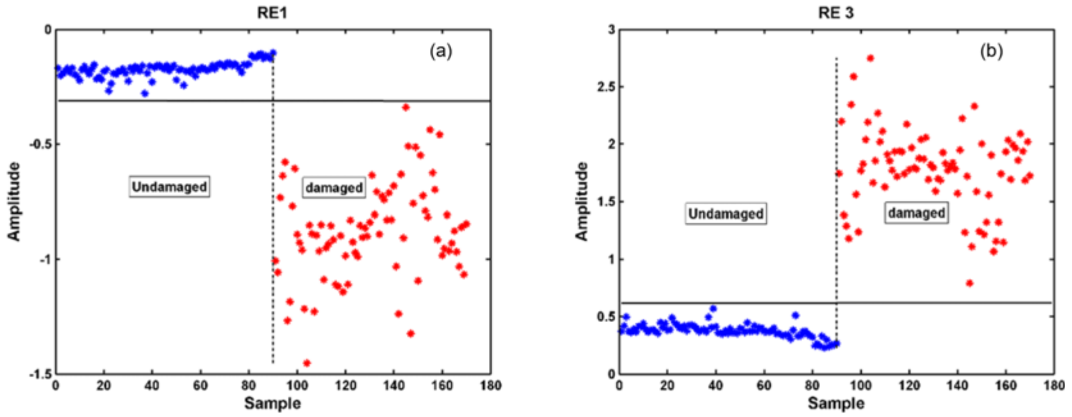


Fig. 12. Amplitudes from Damaged and Undamaged Condition: (a) RE_1, (b) RE_3

thresholds but both exhibit the significant difference in data trend to allow clear identification for undamaged or damaged structures. Clearly, both AR and RE features enable identifying damages. The RE_1 and RE_3, illustrated in Figs. 12(a) and 12(b), display even higher sensitive in identification to undamaged or damaged cases as expected.

5.2 Effectiveness of the Optimization for SVM Parameters

To assess the effectiveness of different optimization techniques for the SVM parameters, the 3rd floor's data are separated into two groups randomly, while each group with five testing results for each experiment scenario, referred as the training group and testing group, respectively. The training group is to construct the model and tailor to select the optimized parameter(s). The parameters C and γ of the RBF kernel functions are optimized through the GS, PSO and GA techniques, respectively, which were addressed in detail below.

In the GS-SVM technique, to obtain the best parameters C and

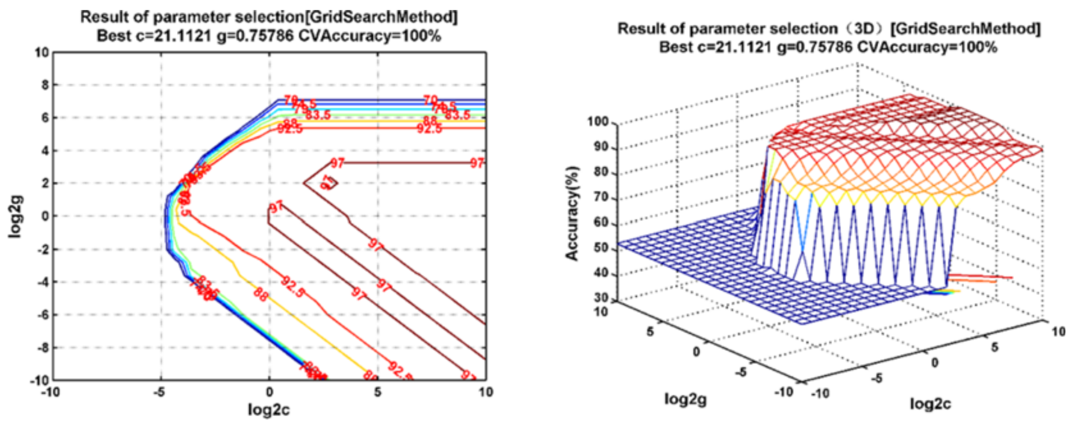


Fig. 13. 2D Line and 3D Contour of Parameter Selection for AR using the GS Technique

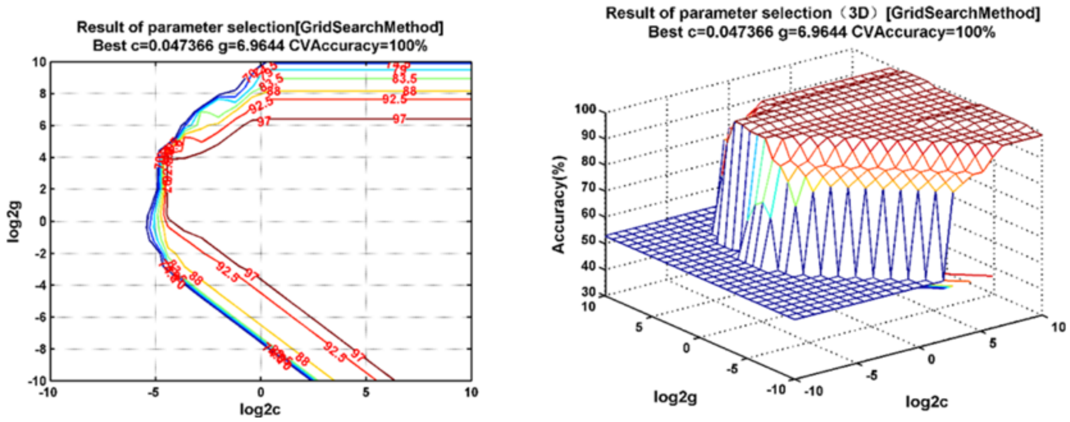


Fig. 14. 2D Line and 3D Contour of Parameter Selection for RE using the GS Technique

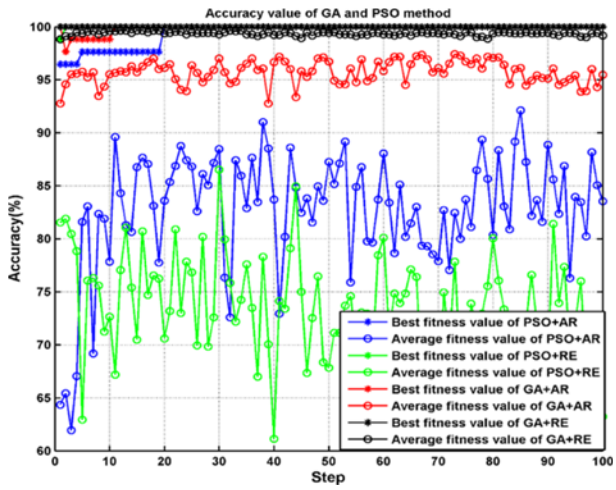


Fig. 15. Best Fitness Value and Averaged Fitness Values using PSO and GA for AR and RE

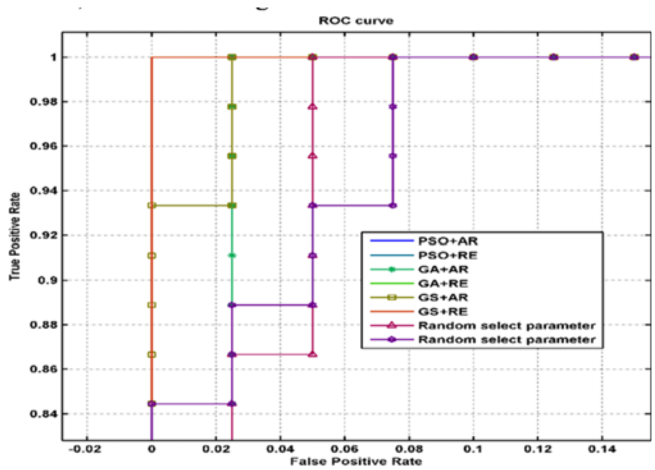


Fig. 16. ROC Curves for the PSO+SVM, GA+SVM, GS+SVM Algorithms Based on AR and RE

γ, a rough range of C and γ was selected as (2^{-10}, 2^{-9},..., 2^{10}), which were modified to the range (2^{-2}, 2^{-1}, ... 2^{4}), and all of the variables are plot in Figs. 13 and 14. The K-fold cross validation (K-CV) and GS-SVM are used for every possible value of the parameters (C, γ). Although figures for the AR and RE parameters in terms of 2D line and 3D contour exhibit different configurations, both maximum contour lines reach up to the same value of 97 percent, which confirms that both have the superior accuracy as damage sensitive features, when proper parameters C and γ are selected.

In the PSO-SVM technique, PSO algorithm has a swarm size of 60 particles. The initial C and γ are 1.5 and 1.7, respectively. The searching ranges are: C ranging [0.1 100] and γ ranging [0.1 1000] and the iteration step is 100. Three subsets are selected for the cross validation method. The velocity relationship is $V = KX$, where K ranges [0.1 1.0]; the parameter before the velocity w is [0.8 1.2]. In the GA-SVM technique, the population size is [20 100] and the searching ranges are C ranging [0 100] and γ ranging [0 1000]. Five subsets are used for the cross validation method. The fitness value denotes the accuracy. Fig. 13 plots eight cases for both optimization methods, where the best accuracy and the average accuracy per iteration are defined as criteria. Clearly, the GA approach converged better accuracy than that of the PSO, and using RE_i feature converaged better than AR_i feature. The lowest converged value is using PSO+RE_i, while the highest converged value is the method of the GA+RE_i. The best fitness values for both optimization methods can reach up to one hundred percent.

5.3 Accuracy of Damage Detection Methods

To further verify the accuracy of each SVM method herein, the Receiver Operating Characteristic (ROC) curve is used to qualify how accurately damage identification for distinguishing between undamaged and damaged cases. The ROC curves of testing group are plotted for all eight cases, as shown in Fig. 16.

Note that if the curve jumps through the left-upper corner point at (0, 1), it means the damage classification is perfect in accuracy. Qualitatively, the ROC curves revealed that PSO+AR, PSO+RE, GA+RE, GS+RE have a perfect classification. Furthermore, GA+AR and GS+AR cannot have a perfect classification. As illustrated in Fig. 16, if the parameters C and γ are selected randomly (without optimization), the classification results

Table 4. The Value of Optimized Parameter and Test Accuracy

Feature and optimization method	Optimized parameter and Test accuracy		
	Best c	Best γ	Test accuracy (%)
AR parameter + PSO	60.10	0.42	97.65
AR parameter + GA	30.52	0.48	97.65
AR parameter + GS	21.11	0.76	98.82
Residual statistical feature +PSO	0.10	11.09	100.00
Residual statistical feature +GA	0.44	4.45	100.00
Residual statistical feature +GS	0.25	4.00	100.00

yielded the worst case than any of results using the optimization methods as expected, which also suggests the importance of the optimization for the SVM. Moreover, the optimized damage sensitive feature REs have a 100% accuracy, regardless of any kind of the optimization methods, thereby highlighting the key point for selection of suitable damage features toward the accuracy of classification.

Table 4 shows the result of optimized parameters and their accuracy as compared to train data under different optimization methods and different damage features. The optimized parameters are different to different approaches, as observed from Figs. 13 and 14. The contour figure shows the range of the perfect parameters that float in a lager range. Table 4 demonstrates that the best optimization methods for testing accuracy is the grid-search method, while all optimization methods will maintain the highest accuracy if the RE features are selected.

6. Conclusions

This study presents the performance of the optimization-based machine learning (GS+SVM, PSO+SVM, GA+SVM) using two damage sensitive features (AR and RE) for damage detection. To avoid the overfitting for the SVM model, the cross-validation method is used to get the most reasonable parameters for predicting the test data, while the ROC curves are used as tools to quantify the accuracy of the optimization based SVMs. Some conclusions can be drawn as follows:

1. The optimization method based SVMs exhibit high accuracy to allow distinguishing between undamaged and damage cases, even when there are interferences such as operational and environmental conditions.
2. Results have demonstrated the importance of selection of damage features for damage detection. Clearly, the RE feature based SVM has significantly higher accuracy than that of AR type. The testing results of RE based SVM reach up to one hundred percent to training data in all cases, suggesting that the RE is more sensitive to the nonlinear response due to damages, which is confirmed from all cases. Therefore, selecting a better damage features is key to yield a good damage classification.
3. Among the three proposed optimization algorithms, GS, PSO and GA, the GS has the better accuracy of data classification. The reason is because the GS are parallelized and it has independent parameters, which is hard to be achieved by using GA or PSO. However, the GS may cost more computation time as compared to the GA or PSO, if higher amount of parameters are optimized.
4. Comparison of the average accuracy and best accuracy for the GA and PSO revealed that although the best accuracy of the CV subset is almost the same, the average value of the CV subset accuracy is different to each other. Clearly, PSO and GA has different number of subset (PSO is 3 and GA is 5), suggesting that the GA requires less amount of sample in each subset and thus it will be more robust. Also, the GA will yield the higher accuracy in average when it has the same amount of subset as that of PSO.

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