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Modeling and assessment of VWNN for signal processing of structural systems

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Abstract. This study aimed to develop a model to accurately predict the acceleration of structural systems during an earthquake. The acceleration and applied force of a structure were measured at current time step and the velocity and displacement were estimated through linear integration. These data were used as input to predict the structural acceleration at next time step. The computation tool used was the Volterra/Wiener neural network (VWNN) which contained the mathematical model to predict the acceleration. For alleviating problems of relatively large-dimensional and nonlinear systems, the VWNN model was utilized as the signal processing tool, including the Taylor series components in the input nodes of the neural network. The number of the intermediate layer nodes in the neural network model, containing the training and simulation stage, was evaluated and optimized. Discussions on the influences of the gradient descent with adaptive learning rate algorithm and the Levenberg-Marquardt algorithm, both for determining the network weights, on prediction errors were provided. During the simulation stage, different earthquake excitations were tested with the optimized settings acquired from the training stage to find out which of the algorithms would result in the smallest error, to determine a proper simulation model.

Keywords: gradient descent with adaptive learning rate algorithm; Levenberg/Marquardt algorithm; modeling; Taylor series; Volterra/Wiener neural network

1. Introduction

Periodic structural health monitoring was necessary to secure the safety and maintain the serviceability of structures (Park *et al*. 2007). Structural health monitoring methods would be chosen based on materials used for structures, monitoring ranges, and purposes. Examples included the structural acceleration prediction (Pei *et al*. 2004), concrete damage monitoring (Park *et al*. 2006), restoring force prediction (Lin and Chen 2009, Kosmatopoulos *et al*. 2001). This study aimed to establish a model to accurately predict structural accelerations during earthquakes. The Volterra/Wiener neural network (VWNN) was utilized as the computation tool. The VWNN model was often used to mitigate the problems of non-linear dynamic systems (Kosmatopoulos *et al*. 2001) and was thus adopted to evaluate the influences of Taylor series components in the input nodes, the number of intermediate layer nodes, and the computation algorithms on relative errors of predictions in this study, so that the signal processing of structural systems (Lin 2010, 2011) can be effectively achieved.

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Increasing emphases have been placed on structural health monitoring especially after earthquakes such as the Chi-Chi Earthquake in Taiwan. Besides damages caused by earthquakes, there were still several hidden factors for structures that caused structural responses different from those calculated at the design stage; for instance, simplified assumptions made in structural modeling, differences between the design drawings and the built structure, and the stochastic nature of environmental loads and service loads (Park *et al*. 2007). For the purpose of structural health monitoring, an automated method for tracking the health of a structure combing damage detection algorithms with structural monitoring systems was developed (Lynch and Loh 2006). An example with simulated data demonstrated the efficiency of the neural network in predicting structural accelerations (Pei *et al*. 2004). An impedance-based damage detection technique utilizing a piezoelectric ceramic material evolved as a new tool for the implementation of a built-in diagnostic system (Park *et al*. 2006). A model based adaptive approaches for the on-line identification of hysteretic systems subjected to stochastic dynamic environments have emerged (Kosmatopoulos *et al*. 2001).

Neural networks were favored problem-solving approaches because of their nonlinearity, adaptivity, input/output mapping, evidential response, contextual information, and fault tolerance (Haykin 1994). Volterra and Wiener neural networks (VWNNs) presented a kind of neural networks. The Volterra and Wiener approach could be treated as a special case of a kernel regression framework (Franz and Schölkopf 2006). The structure of the Volterra and Wiener series, modeling the relationship between system response and input in terms of series of first and higher order convolution integrals, provided analytical platforms that could be used for parameter estimation (Vyas and Chatterjee 2011) and adaptive filtering (Kosmatopoulos *et al*. 2001). Although Volterra and Wiener approaches were popular, their applications were limited to relatively low-dimensional and weakly nonlinear systems because of the increasing number of terms that had to be estimated (Franz and Schölkopf 2006). Yet, the use of Taylor methods for differential-algebraic equations provided with excellent results (Barrio *et al*. 2011).

Based on the arguments above for the advancement of signal processing of structural systems for structural health monitoring, the modeling of VWNN was considered to predict structural accelerations followed by the assessment of the entire signal processing approach. In this study, signal preprocessing included the measurement of structural acceleration and applied force at current time step and the estimation of structural velocity and displacement through linear integration using a VW filter. These data were used as input data to predict structural acceleration at next time step. For acquiring accurate predictions of structural accelerations as well as alleviating problems of relatively large-dimensional and nonlinear systems, the VWNN model was adopted as the fundamental signal processing tool with the addition of Taylor series expansion test, together with two other tests for evaluation purposes. The first test was to find out if applying the Taylor series would assist to reduce relative errors of predictions by comparing model outputs with actual outputs. The second test was to search for an optimal empirical formula involving the number of intermediate layer nodes in the VWNN, since the output could be influenced by the selection of intermediate layer nodes and by the adopted estimation algorithms. The third test was to evaluate the influences of two algorithms for determining the network weights, including the gradient descent with adaptive learning rate (GDA) algorithm and the Levenberg-Marquardt (LM) algorithm, on prediction errors for successful signal processing of structural accelerations.

2. Structural dynamics presentation for acceleration prediction

Since this study aimed to develop a model to accurately predict the acceleration of structural systems during an earthquake, a formula for acceleration prediction was required according to the structural dynamics proposed by Pei *et al*. (2004)

$$x_1''(t) = M_{11}^{-1} f_1(t) - M_{11}^{-1} r(t) \tag{1}$$

where $x_1''(t)$ is the acceleration of a structure (e.g., shear-type building) induced by earthquake, M_{11} is a matrix representing the weight of each floor, r(t) is the restoring force with unknown properties, and $f_1(t)$ is the excitation force on the structure. The acceleration and applied force of the structure were measured at current time step and the velocity and displacement were estimated through linear integration. The restoring force was estimated using the velocity and displacement (Pei *et al*. 2004) and was written as

$$r'(t) = Q(r(t), x_1(t), x_1'(t)) \tag{2}$$

where Q is a continuous function, noting that this function is not exhaustive as more independent variables can be added to represent more complicated nonlinearities. Pei *et al*. (2004) further applied linear difference equation for approximation of Eq. (2), and with simple algebra operations, it was possible to obtain

$$[Q(r(t_n), x_1(t_n), x_1'(t_n)](t_{n+1} - t_n) + r(t_n) = r(t_{n+1}) \tag{3}$$

where $r(t_n)$ is the restoring force at the current time step t_n, and $r(t_{n+1})$ is the restoring force at the next time step t_{n+1}. The time interval $(t_{n+1} - t_n)$ is constant. Plugging the information of $r(t_{n+1})$ in Eq. (3) into Eq. (1) yielded

$$x_1''(t_{n+1}) = M_{11}^{-1} f_1(t_{n+1}) - M_{11}^{-1}\{[Q(r(t_n), x_1(t_n), x_1'(t_n))](t_{n+1} - t_n) + r(t_n)\} \tag{4}$$

With the substitution of $r(t_n)$ in Eq. (4) by using the r(t) in Eq. (1) and letting $t = t_n$ in Eq. (1), it was possible to simplify Eq. (4) as (Pei *et al*. 2004)

$$x_1''(t_{n+1}) = \psi(x_1(t_n), x_1'(t_n), x_1''(t_n), f_1(t_n), f_1(t_{n+1})) \tag{5}$$

where Ψ is an unknown non-linear continuous function.

3. Neural network construction

A neural network was considered a massively parallel distributed processor that possessed a natural propensity for storing experiential knowledge and enabling the network for learning (Haykin 1994). The neural network has been broadly applied in fields such as biology, economics, engineering, and medical science. To obtain accurate predictions of structural accelerations for non-linear systems, the neural network model was adopted as the signal processing tool in this study.

3.1 Volterra and Wiener neural network (VWNN)

Since signal preprocessing included the measurement of structural acceleration and applied

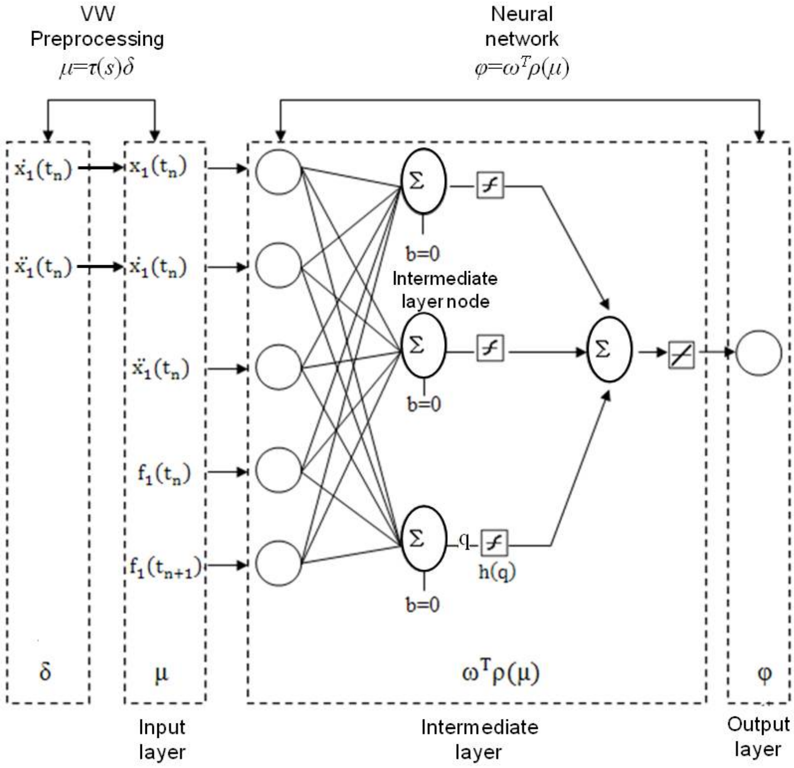

Fig. 1 Volterra and Wiener neural network (VWNN)

force at the current time step as well as the estimation of structural velocity and displacement through linear integration using a Volterra and Wiener (VW) filter, the Volterra and Wiener neural network (VWNN), as shown in Fig. 1, was considered. Inputs to the network included the structural displacement, structural velocity, structural acceleration, and the excitation force at the current time step, as well as the excitation force at the next time step. The output was the structural acceleration at the next time step for the purpose of acceleration predictions.

The VWNN consisting of a linear multi-input multi-output (MIMO) stable dynamical system connected in cascade with a linear-in-the-weights neural network. The dynamics of the linear MIMO system, as in Fig. 1, could be described as (Kosmatopoulos *et al*. 2001)

$$\varphi = \omega^T \rho(\tau(s)\delta) \tag{6}$$

where δ denotes the inputs to the input layer of VWNN, $\tau(s)$ denotes a stable transfer function matrix, ρ denotes a function of μ whose outcome are the input nodes in the intermediate layer of VWNN, and ω indicates the synaptic weights of the neural network while φ indicates the output of the neural network (Kosmatopoulos *et al*. 2001).

In the training process of the neural network, the selection of the transfer function was significantly important. An inappropriate transfer function might cause the network convergence process relatively slow (Gao and Chen 2011). This study selected the linear transfer function (linear integral) in the input layer and the hyperbolic tangent sigmoid transfer function in the intermediate layer of the network (Fig. 1), respectively. The hyperbolic tangent sigmoid transfer function was computed as follows

$$h(q) = \frac{2}{1 + e^{-2q}} - 1 \tag{7}$$

where q denotes the input while h(q) denotes the output after passing through the transfer function (Adnani *et al.* 2011). Through the hyperbolic tangent sigmoid transfer function, mitigating the non-linearity problems of multi-layer neural networks, the output data are confined in values between 1 and -1.

3.2 Adoption of Taylor series

In addition to the adoption of the VWNN model, the Taylor series was also incorporated into the modeling process to acquire accurate predictions of structural accelerations. The quality of the nonlinear black-box modeling process was always a result of a certain compromise between the "expressive power" of the model to be identified and the measurement error (Lin and Chen 2009). The incorporation of the Taylor series would be beneficial not only to the reduction of modeling error but also to the evaluation of large space systems where several degrees of freedom and related parameters were to be estimated. The Taylor series, after omitting the cross components in the power series (Lin and Chen 2009), was thus applied to the network for the acceleration prediction. According to the definition of Taylor series

$$f(x) = \sum_{i=1}^{HO} a_i (x - c)^i \tag{8}$$

where c is any arbitrary constant, HO is the highest order and usually defined by users, and x is an independent variable. The function f(x) is represented in a polynomial series function. With c = 0, Eq. (8) becomes

$$f(x) = \sum_{i=1}^{HO} a_i (x)^i \tag{9}$$

Thus the formula used to predict the structural acceleration (Eq. 5) can be expressed using the Taylor series as follows

$$\begin{gathered} x_1''(t_{n+1}) = \psi(x_1(t_n), x_1'(t_n), x_1''(t_n), f_1(t_n), f_1(t_{n+1})) = \\ \sum_{i=1}^{HO} [a_1(x_1(t_n))^i + a_2(x_1'(t_n))^i + a_3(x_1''(t_n))^i + a_4(f_1(t_n))^i + a_5(f_1(t_{n+1}))^i] \end{gathered} \tag{10}$$

Virtually, the larger HO is, the Taylor series expansion is more capable of approximating Ψ in Eq. (10). A higher order of Taylor series leads to a higher number of input nodes in the intermediate layer of VWNN (Fig. 1). For example, a 3rd-order Taylor series expansion includes 15 input nodes in this study. On the other hand, computer calculation may result in a round-off error, which increases as the order increases. Hence, higher order of the Taylor series expansion does not necessary give better results.

To reduce relative errors of predictions by comparing model outputs with actual outputs, the optimal order of the Taylor series expansion should be acquired through various order tests. Further, an optimal empirical formula for the number of intermediate layer nodes of the VWNN is required because the output of the network depends on the selection of intermediate layer nodes.

3.3 Number of intermediate layer nodes

Choosing one intermediate layer (Fig. 1), various trials conducted in this study to determine the optimal number of nodes in the intermediate layer of the neural network include

(1) If the neural network is used to predict structural accelerations, the number of nodes in the intermediate layer can be $3N_i + 2N_f$, where N_i is the degrees of freedom of the system and is regarded as the number of nodes in the output layer, while N_f is the degrees of freedom when the excitation force is applied and is regarded as the number of applied force nodes in the input layer (Pei *et al*. 2004).

(2) If a considered system belongs to a general system, the number of nodes in the intermediate layer can be $N_1 + N_2$, where N_1 is the number of nodes in the input layer and N_2 is the number of nodes in the output layer (Masri *et al*. 1999).

(3) If a considered system belongs to a complicated system, the number of nodes in the intermediate layer can be $(N_1 + N_2) * 2$, where N_1 is the number of nodes in the input layer and N_2 is the number of nodes in the output layer (Peng 2010).

(4) If a considered system belongs to an easy system, the number of nodes in the intermediate layer can be $(N_1 + N_2)/2$, where N_1 is the number of nodes in the input layer and N_2 is the number of nodes in the output layer (Peng 2010).

(5) Also, the trial number of nodes in the intermediate layer can be $(N_1 + N_2)^{1/2}$, where N_1 is the number of nodes in the input layer and N_2 is the number of nodes in the output layer (Yeh 2003).

Discussions have been provided on the influence of the number of nodes in the intermediate layer on prediction errors in order to search for a minimum relative error. Furthermore, the output of VWNN also depends on its estimation algorithm for determining the network weights.

4. GDA algorithm and LM algorithm

Two of the neural network algorithms used in the assessment of prediction errors are introduced. The first algorithm is the gradient descent with adaptive learning rate (GDA) algorithm. Although there were varieties of learning algorithms available, the major of them, which included the popular back propagation learning algorithm, were of the gradient descent type (Qian 1999). In gradient-based techniques, a performance criterion was defined based on the error between the network and actual response in terms of mean square errors

$$J = \left\| \ddot{x}(t_{n+1}) - a_{n+1} \right\|^2 \tag{11}$$

where $\ddot{x}(t_{n+1})$ denotes the network output and a_{n+1} denotes the actual output. Since $\ddot{x}(t_{n+1})$ depended on the network parameters, the value of J could be decreased if the network weights were revised in the direction of the negative gradient of the performance function (Masri *et al*. 1999). The GDA algorithm was a performance of the steepest descent algorithm with changing learning rate during the training process (MathWorks 1994), in which the steepest descent algorithm recalculated the weights at time step t

$$\Delta w_t = -\varepsilon \Xi_w E(w_t) \tag{12}$$

where ε denotes the learning rate while Ξ_w denotes the gradient operator with respect to the weights and $E(w_t)$ is the error function. The gradient of the error function with respect to each weight was then computed and the weights were modified along the downhill direction of the gradient in order to reduce the error (Qian 1999). The gradient descent techniques utilized only first derivation information, while others could be derived that utilized second- and higher-order derivation information (Masri *et al*. 1999).

The second algorithm is the Levenberg/ Marquardt (LM) algorithm. The LM algorithm was widely used and recognized as very efficient for solving the problem of minimizing non-linear minimum squares (De Oliveira 2011). The LM algorithm manifested the most efficient convergence during the back propagation training process since it acted as a trade-off between the first-order optimization method (steepest-descent algorithm) with stable but slow convergence and the second-order optimization method (Gauss-Newton method) with opposite characteristics (Chen *et al*. 2003). The mathematical form of the LM algorithm can be expressed as

$$\mathrm{w_k} - [\mathrm{J^T J} + \lambda_\mathrm{k}\mathrm{diag}(\mathrm{J^T J})]\mathrm{J^T e} = \mathrm{w_{k+1}} \tag{13}$$

where $\mathrm{w_k}$ is the weights and $\mathrm{w_{k+1}}$ is the new weights, k is the iteration step, J is the Jacobian Matrix, e is the error vector, and λ_k is a scalar that controls convergence properties (Lautour and Omenzetter 2010). When using the LM algorithm for neural network training, however, some disadvantages appeared in the numerical computations. Large memory was required for matrix operations at each iteration process, and large error oscillations during the standard LM training process frequently occurred (Chen *et al*. 2003).

Discussions on the influences of the GDA algorithm and the LM algorithm on prediction errors were provided so as to choose an algorithm to achieve the smallest error possible.

5. Numerical results and discussions

The data used in this study were measured through experiments conducted in the civil engineering department of Feng Chia University, Taiwan. A 30%-scaled steel structure of a 3-floor building was placed on a shaking table. Each floor of the structure was designed with beams, columns, and slabs. The weight of the first, second, and third floor was estimated as 530.65 kg, 530.65 kg, and 514.67 kg, respectively. Since the adopted VWNN model for the prediction of structural accelerations contained the training and simulation stage, the training stage was discussed to search for optimized settings used for the simulation stage. During the simulation stage, different earthquake excitations were tested with the optimized settings obtained from the training stage to determine a proper simulation model.

5.1 Training stage of VWNN

Using MATLAB R2010a software, the data at the training stage of neural network were divided

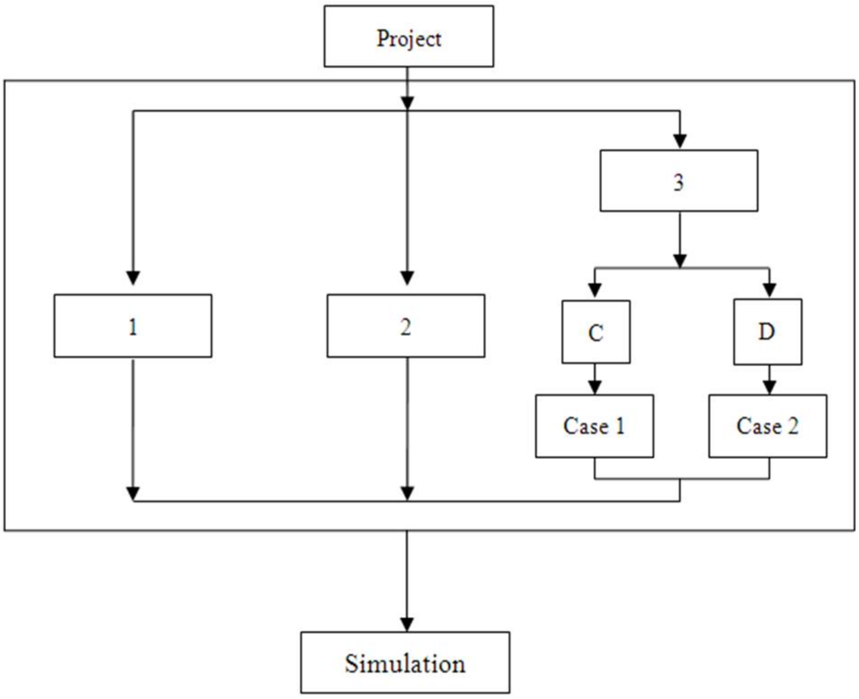

Fig. 2 Simulation after test projects with cases as in Table 1

into portions of 70% for training, 15% for validation, and of 15% for testing. Three projects with two cases were designed for test as listed in Table 1. Fig. 2 shows the simulation after test projects with cases as in Table 1. The relative errors of the two cases were compared to find out which one would be better. Numerical results of the minimum relative errors of acceleration predictions using different number of nodes in the intermediate layer of VWNN at the training stage were listed in Table 2. Details of the projects and results were described as follows.

Project 1

The first test was to find out if applying the Taylor series expansion to the input nodes in the intermediate layer of VWNN (Fig. 1) would assist to reduce relative errors of predictions by comparing model outputs with actual outputs. The influences of various orders from one to ten of Taylor series expansion on prediction errors were compared to determine which order could result in the smallest error. Orders higher than ten were not considered since as the order increased, the training time increased and the round-off error interfered. It was addressed that minimum prediction errors were often reached using 3rd-order Taylor series model (Lin and Chen 2009). The test results were shown in Figs. 3-7, each with different number of intermediate layer nodes. When the GDA algorithm was applied, the prediction error could not be reduced as the order increased, demonstrating that the Taylor series was not suitable for the GDA algorithm to improve the prediction accuracy of structural accelerations. When the LM algorithm was applied, the prediction error was reduced as the order increased and then began to increase after a certain order, demonstrating that the Taylor series was suitable for the LM algorithm to reach minimum relative errors of acceleration predictions.

Table 1 Test projects with control factor

Project	Control factor	Case 1	Case 2
1	A. Using various Taylor series order	✔	✔
2	B. Designing different number of nodes in the intermediate layer of VWNN	✔	✔
3	C. Using the gradient descent with adaptive learning rate (GDA) algorithm	✔	
	D. Using the Levenberg/Marquardt (LM) algorithm		✔

(Note: ✔ indicates the control factor corresponding to the case)

Table 2 Minimum relative errors of acceleration predictions using different number of nodes in the intermediate layer of VWNN at the training stage

Number of nodes in the intermediate layer	Minimum error	Optimal algorithm	Optimal Taylor series order
$3N_i + 2N_f$	0.0362	LM	7
$(N_1 + N_2)$	0.0264	LM	5
$(N_1 + N_2) * 2$	0.0258	LM	4
$(N_1 + N_2)/2$	0.0287	LM	9
$(N_1 * N_2)^{1/2}$	0.0402	LM	10
Optimal setting			
$(N_1 + N_2) * 2$	0.0258	LM	4

(Note: Minimum relative errors in terms of RMS, to the third non-zero digit)

Project 2

The second test was to search for an optimal empirical formula regarding the number of intermediate layer nodes in the VWNN, since the output could be influenced by the selection of intermediate layer nodes in addition to the adopted estimation algorithm. The results were summarized in Table 2. It was found that the relative error was minimal with the number of nodes in the intermediate layer being $(\mathrm{N}_1 + \mathrm{N}_2) * 2$, implying that the problem of acceleration prediction belonged to a complicated system. Different number of intermediate layer nodes corresponded to different optimal Taylor series order, which increased from 5 to 7, 9, and 10 with respective number of intermediate layer nodes being $(\mathrm{N}_1 + \mathrm{N}_2)$, $3\mathrm{N}_\mathrm{i} + 2\mathrm{N}_\mathrm{f}$, $(\mathrm{N}_1 + \mathrm{N}_2)/2$, and $\sqrt{\mathrm{N1} * \mathrm{N2}}$. If a small number of intermediate layer nodes were used, the neural network could be limited and not able to solve complicated systems.

Project 3

The third test was to evaluate the influences of the GDA algorithm and the LM algorithm, both for estimating the network weights, on relative errors for successful signal processing of structural

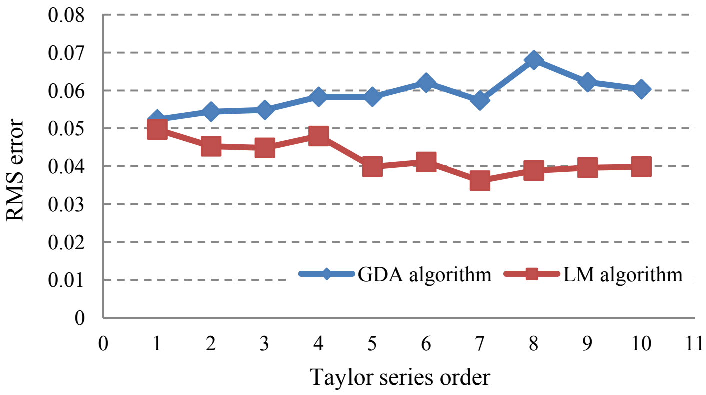

Fig. 3 Influence of various Taylor series order on relative error of acceleration predictions with the number of intermediate layer nodes = $3N_i + 2N_f$

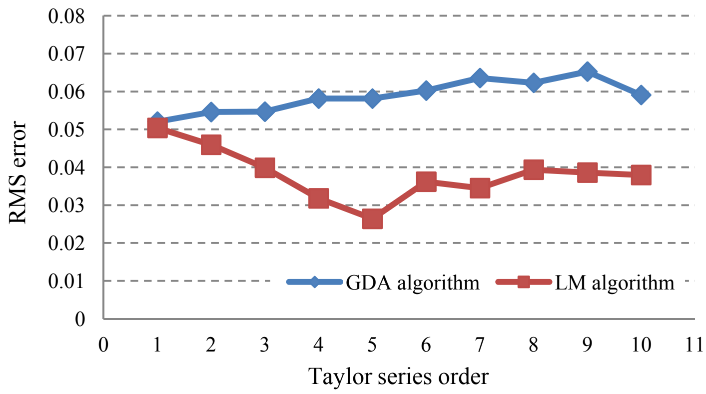

Fig. 4 Influence of various Taylor series order on relative error of acceleration predictions with the number of intermediate layer nodes = $(N_1 + N_2)$

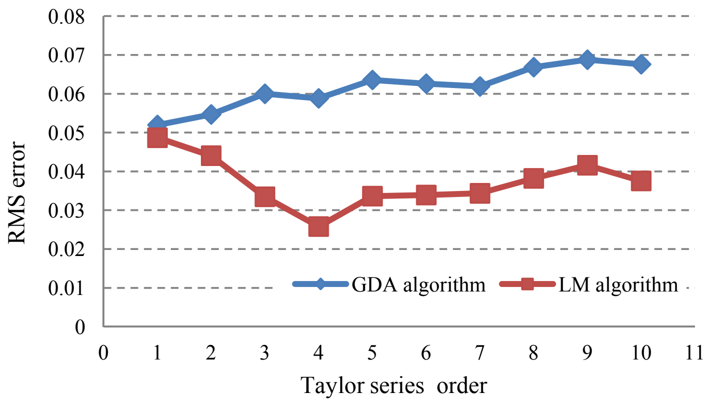

Fig. 5 Influence of various Taylor series order on relative error of acceleration predictions with the number of intermediate layer nodes = $(N_1 + N_2) * 2$

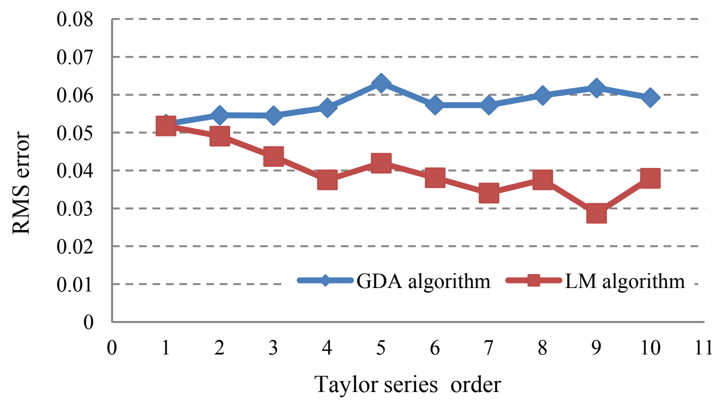

Fig. 6 Influence of various Taylor series order on relative error of acceleration predictions with the number of intermediate layer nodes = $(N_1 + N_2)/2$

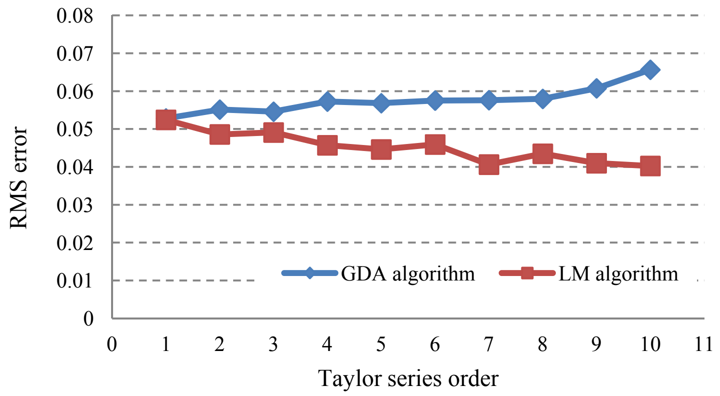

Fig. 7 Influence of various Taylor series order on relative error of acceleration predictions with the number of intermediate layer nodes = $(N_1 * N_2)^{1/2}$

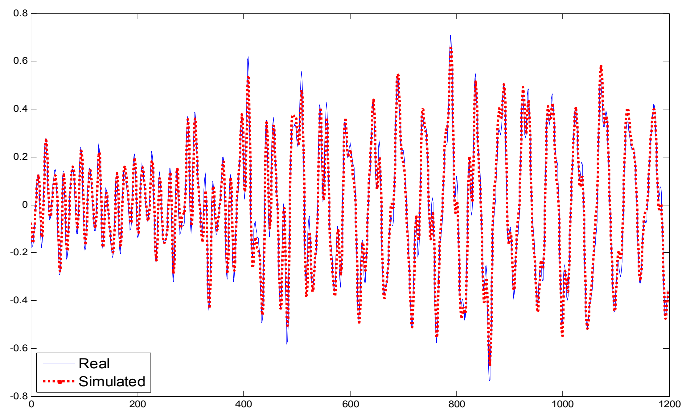

Fig. 8 Simulated accelerations using the Chi-chi earthquake excitations, with the number of intermediate layer nodes being $(N_1 + N_2) * 2$, the GDA algorithm, Taylor series order = 1, and the training data using the California earthquake excitations

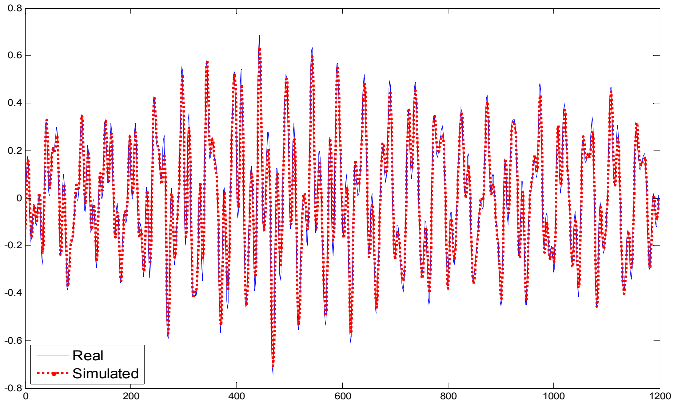

Fig. 9 Simulated accelerations using the California earthquake excitations, with the number of intermediate layer nodes being $(N_1 + N_2) * 2$, the GDA algorithm, Taylor series order = 1, and the training data using the Chi-chi earthquake excitations

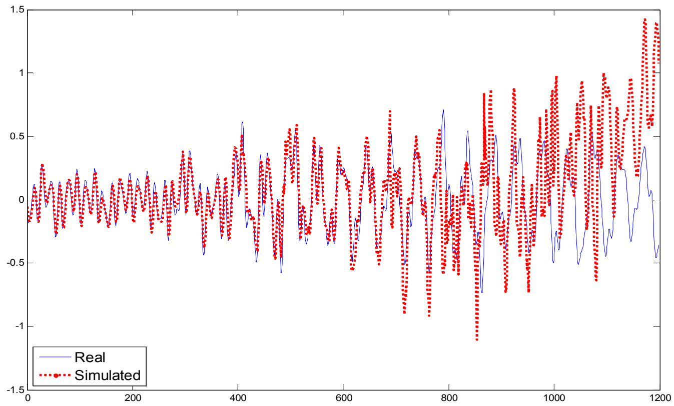

Fig. 10 Simulated accelerations using the Chi-chi earthquake excitations, with the number of intermediate layer nodes being $(N_1 + N_2) * 2$, the LM algorithm, Taylor series order = 4, and the training data using the California earthquake excitations

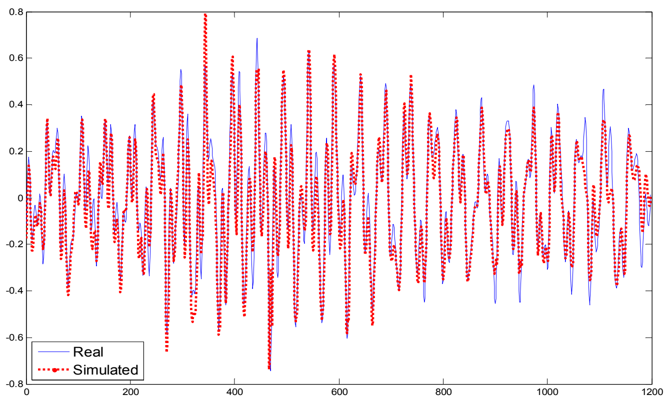

Fig. 11 Simulated accelerations using the California earthquake excitations, with the number of intermediate layer nodes being $(N_1 + N_2) * 2$, the LM algorithm, Taylor series order = 4, and the training data using the Chi-chi earthquake excitations

Table 3 Results of simulations

Case	A	B	C	D
RMS error	0.04899	0.05831	0.3762	0.09327
Average	0.05365		0.2347	

(Note: Prediction errors in terms of RMS, to the forth non-zero digit)

accelerations. The results were listed in Table 2, illustrating that the optimal algorithm was the LM algorithm compared to the GDA algorithm and the difference was significant. Hence, the LM algorithm was a better choice for the VWNN at the training stage.

Just for comparison purposes, the prediction error of Case 2 (Table 1) using the VWNN model in general was 50% reduced than the work of Pei *et al*. (2004). In practice, such a developed VWNN model can be applied to off-line modify structural accelerations.

5.2 Simulation stage of VWNN

During the simulation stage, different earthquake excitations, including California earthquake and the Chi-chi earthquake, were tested with the optimized settings obtained from the training stage to find out which of the algorithms would result in the smallest error, to determine a proper simulation model. The test cases were described as follows.

Case A

With the number of intermediate layer nodes being $(N_1 + N_2) * 2$, the GDA algorithm, Taylor series order = 1, and the training data using the California earthquake excitations while the simulation data using the Chi-chi earthquake excitations, the simulation results were shown in Fig. 8.

Case B

With the number of intermediate layer nodes being $(N_1 + N_2) * 2$, the GDA algorithm, Taylor series order = 1, and the training data using the Chi-chi earthquake excitations while the simulation data using the California earthquake excitations, the simulation results were shown in Fig. 9.

Case C

With the number of intermediate layer nodes being $(N_1 + N_2) * 2$, the LM algorithm, Taylor series order = 4, and the training data using the California earthquake excitations while the simulation data using the Chi-chi earthquake excitations, the simulation results were shown in Fig. 10.

Case D

With the number of intermediate layer nodes being $(N_1 + N_2) * 2$, the LM algorithm, Taylor series order = 4, and the training data using the Chi-chi earthquake excitations while the simulation data using the California earthquake excitations, the simulation results were shown in Fig. 11.

Table 3 listed the simulation results of Case A-D. It was noted that the GDA algorithm (Case A and B, with smaller prediction errors) was better than the LM algorithm (Case C and D) for the simulation stage of VWNN. The averaged RMS error of the GDA algorithm was decreased by 77% when compared to the LM algorithm with fourth-order Taylor series model. In practice, the GDA algorithm with first-order Taylor series model, along with the number of intermediate layer nodes of VWNN being $(N_1 + N_2) * 2$, can be utilized for simulating different earthquake excitations.

6. Conclusions

This study utilized the Volterra/Wiener (VW) signal preprocessing filter to add the ability of the neural network (NN) for solving non-linear problems so as to predict structural accelerations for structural health monitoring. In order to improve the accuracy of signal processing, the adoption of Taylor series model, different number of intermediate layer nodes in NN, and the influence of different algorithms on prediction errors (differences between model and actual outputs) have been assessed.

During the training stage of VWNN, it was concluded to adopt the fourth-order Taylor series model, the number of nodes in the intermediate layer of NN being $(\mathrm{N}_1 + \mathrm{N}_2) * 2$, and the Levenberg/ Marquardt (LM) algorithm. The prediction error was efficiently reduced by 50%. In practice, such a developed VWNN model can be applied to off-line modify structural accelerations. Although the LM algorithm could lead to smaller error during the training stage, the resulting averaged error with this algorithm was larger during the simulation stage of VWNN. During the simulation stage, the averaged RMS error of the GDA algorithm was decreased by 77% when compared to the LM algorithm with fourth-order Taylor series model. In practice, the GDA algorithm with first-order Taylor series model, along with the number of intermediate layer nodes of VWNN being $(\mathrm{N}_1 + \mathrm{N}_2) * 2$, can be utilized for simulating different earthquake excitations so as to predict structural accelerations.

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