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Dynamic neural modeling of fatigue crack growth process in ductile alloys

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ABSTRACT

In this paper, the dynamic neural modeling of fatigue crack growth process in ductile alloys is studied. It is shown that a fatigue crack growth process is treated as a virtual nonlinear dynamic system. A nonlinear model can then be developed with two dynamic neural networks (DNNs), designed to learn the dynamics of crack opening stress and crack length growth, respectively. The DNNs are constructed by adding the tapped-delay-line memories to both the input and the output layers of conventional single layered feed-forward neural networks (SLFNs). Since the delayed output feedback components are placed in parallel with the hidden nodes, a generalized hidden layer is formulated. The DNNs are then trained in the sense that the input weights of the DNNs are uniformly randomly selected in a range, and the generalized output weights are globally optimized with the batch learning type of least squares. The well-trained dynamic neural model is capable of capturing all dynamic characteristics of crack growth process. The excellent performance of the dynamic neural model of fatigue crack growth process is confirmed with the experimental data of 2025-T351 and 7075-T6 aluminum alloy specimens.

1. Introduction

Modeling of fatigue crack growth process in ductile alloys has been attracting a great deal of attention of researchers and engineers. This is because most machines, vehicles and structures in our modern life involve ductile metal components, and the safety, reliability and useful life of these components directly or indirectly affect the quality of our daily life. However, it has long been noted that the mechanism of fatigue crack propagation has not been fully understood, and it is necessary to further explore the modeling of fatigue crack growth from the viewpoint of nonlinear dynamic system and artificial intelligence.

In the analysis of fatigue crack growth process in ductile alloys, the crack opening stress and crack length are considered as two state variables, describing the dynamic characteristics of fatigue crack growth process [14,15,18,19]. It is well known that the fatigue crack growth has a complex nonlinear relationship with both the current cyclic stress excitation and the past history of the cyclic stress excitation, crack length and crack opening stress, respectively. The modeling of a

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fatigue crack growth process is usually carried out by recursively fitting two highly non-linear difference equations with the measurements of crack opening stress, crack length, material parameters and recursively computed model parameters. The models are then used to perform the one-step-ahead predictions of crack opening stress and crack growth, respectively [4,14,15,18,19]. The useful life of the ductile material is then estimated on the basis of the time period or the number of loading cycles for the largest undetected crack to grow to failure [20]. However, since the model parameters are recursively computed with empirical data and material parameters, the performances of these models are largely dependent on the accuracy of the measurements of crack length, crack opening stress, yield strength, flow stress, specimen thickness and specimen half-width and so on. In addition, because of the variability and uncertainty, existed in the material parameters and crack growth process, it is often difficult to accurately predict both the crack opening stress and crack length growth by using the existing models.

In addition, a look-up table of the crack length-dependent correction factor, obtained from experiments, is required for recursively computing crack length with the nonlinear model [4,14,15,18,19]. However, such a look-up table may not be very helpful when the working environment as well as the geometry parameters of material is changed.

In this paper, we explore the dynamic neural modeling of crack growth process in ductile alloys. From the viewpoint of engineering systems, we treat a fatigue crack growth process as a virtual uncertain nonlinear dynamic system with two subsystems describing the dynamics of crack opening stress and crack length growth, respectively. A dynamic neural model can then be developed with two DNNs. The first DNN is used to model the dynamics of crack opening stress, with the minimum stress and the maximum stress as the input signals, and the crack opening stress as the output. The second DNN is designed to model the dynamics of crack length growth with the minimum stress, the maximum stress and the crack opening stress as the inputs and the crack length as the output.

The DNNs in this work are constructed by adding the tapped-delay-line memories to both the input and the output layers of the conventional SLFNs. The tapped-delay-line memories at the input layer of the DNNs are short-term memories, windowing the input signals and preserving the past values of the inputs internally in the sense that the output of the DNNs is related to both the current and the past inputs. However, the tapped-delay-line memories located at the output layer of the DNNs introduce the feedback-loops to ensure sure that the outputs of DNNs are not only related to the current inputs and current outputs, but also related to the past inputs and the past outputs.

It is well known that, mathematically, feed-forward neural networks (FFNNs) perform the static mappings from the input space to the output space with the property that the outputs of FFNNs are the functions of the current input patterns, and the output values keep constant if the inputs are constant. Such a time-independent property makes FFNNs to be very useful for pattern classification where the patterns are represented by a set of fixed points in the high dimensional pattern space [6,17]. However, it is difficult for FFNNs to learn so-called time-dependent trajectories for the purpose of complex dynamic system modeling. This is because the behaviors of a dynamic system are described by both its steady states and transient responses, and the system output is not only related to the current input, but also related to the history of the system.

The DNNs or recurrent neural networks (RNNs) with feedback loops are capable of performing time-dependent nonlinear mappings, and thus are able to learn nonlinear dynamic systems through training with a set of desired spatial input and spatial output data pairs over time. Recall that most RNNs are trained recursively with the real-time recurrent learning (RTRL) or the back-propagation through time (BPTT) [6,17]. However, the recursive training processes are time consuming, and the slow convergence has limited their applications, where vast amount of data are presented and fast online training is required.

To overcome the difficulties that are faced by the recursive learning techniques, we will use the random weight learning machines, developed in [1,7,21], to train the DNNs in this work. The learning methodologies proposed in [1,7,21], were initially developed for SLFNs, where the input weights of an SLFN are uniformly randomly selected in a range, and the output weights of the SLFN are then globally optimized with the batch learning type of least squares. However, it will be shown in this paper that, after the delayed output feedback components are placed in parallel with the hidden nodes, a generalized hidden layer is formulated**.** the global training mechanisms in [1,7,21], can also be used to train the DNNs with a set of desired spatial input and output data pairs over time, for achieving a set of globally optimal generalized output weights.

Here we would like to address that, in many applications of the random weight learning for pattern classifications and system modeling, the input weights of SLFNs are often uniformly randomly selected, with the upper and the lower bounds simply set to -1 and 1, respectively, with the result that the outputs of hidden nonlinear neurons are saturated. It has been observed that, for the purpose of pattern classification, such a “random weight selection rule” may be helpful to ensure that all of the feature vectors can be spread out in the feature space, and the features can then be easily classified from the output space of the SLFN classifiers. However, for dynamic modeling of nonlinear systems, the random input weights should be chosen in the sense that the hidden neurons work in the linear region so that the fine changes of the system dynamics can be captured by the neural model. Especially, for the modeling of crack growth process in this work, where the crack length increment is at the level of micro-meter, the random input weights of the DNNs must be chosen such that all of the hidden neurons work in the linear regions for capturing the fine changes of crack growth dynamics.

In nature, the input layer of the DNNs plays the role of mapping the truncated spatial input signal from the input space to the feature space. The output layer can then capture more detailed dynamics of the spatial input signal in the high dimensional feature space. And then, in the batch learning phase, the generalized output weights of the DNNs are globally trained in the sense that the outputs of the DNNs are capable of providing with the optimal approximation to the desired