Multi-time Resolution Ensemble Recurrent Neural Networks for Enhanced Feature Extraction in High-Rate Time Series

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Abstract

Systems experiencing high-rate dynamic events, termed high-rate systems, typically undergo accelerations of amplitudes higher than 100 g in less than 10 ms. Examples include adaptive airbag deployment systems, hypersonic vehicles, and active blast mitigation systems. Given the critical functions of such systems, accurate and fast modeling tools are necessary for ensuring the target performance. However, the unique characteristics of these systems, which consist of 1) large uncertainties in the external loads, 2) high levels of non-stationarities and heavy disturbances, and 3) unmodeled dynamics generated from changes in system configurations, combined with the fast-changing environment limits the applicability of physical modeling tools. In this paper, a neural network-based approach is proposed to model and predict high-rate systems. It consists of an ensemble of recurrent neural networks (RNNs) with short-sequence long short-term memory (LSTM) cells which are concurrently trained. To empower multi step-ahead predictions, the input space for each RNN is selected individually using principal component analysis to extract different resolutions on the dynamics. The algorithm is simulated on experimental data obtained from a high-rate system. Results showed that the quality of step-ahead predictions is significantly improved with respect to a heuristic approach in constructing the input spaces.

Keywords: recurrent neural network, long short-term memory, time series, prediction, high-rate, non-stationary, time series

1. Introduction

High-rate systems are defined as those experiencing dynamic events of typical amplitudes higher than 100 g over durations less 10 ms durations. Examples include adaptive airbag deployment systems, hypersonic vehicles, and active blast mitigation systems. Enabling closed-loop feedback capabilities for high-rate systems could empower their field deployments through enhanced operability and safety. However, this is a difficult task, as these systems are uniquely characterized by 1) large uncertainties in the external loads, 2) high levels of non-stationarities and heavy disturbances, and 3) unmodeled dynamics generated from changes in system configurations [1].

There have been recent research efforts in developing algorithms with real-time capabilities in the high-rate realm, including a sliding mode observer-based algorithm [2], and frequency-based model updating strategy [3]. Others have studied algorithms enabling online identification of highly nonstationary time series, without initial pre-training [4], but the algorithm was not applicable in real-time. Inspired by this algorithm, the authors have proposed an ensemble of recurrent neural networks (RNN) constructed with short-sequence long short-term memory (LSTM) cells to learn nonstationary time series with minimal pre-training. The algorithm showed real-time capabilities with an average computation time of 25 μs, but its multi step-ahead prediction was not evaluated [5]. In this paper, we extend work on the proposed ensemble of RNN for step-ahead prediction. The algorithm is modified to individually select the input space of each RNN, such that different dynamic features are extracted from the time series. The extraction method is based on the embedding theorem, as recently used by others in [6], and principal components analysis (PCA) of the available time series data.

2. Algorithm Architecture

The machine learning algorithm is described in [5]. Briefly, it consists of an ensemble of RNNs constructed with long short-term memory LSTM cells with transfer learning capabilities to cope with the highly limited availability of training data as it is typical for high-rate systems. The use of an ensemble of RNNs empowers multi-rate sampling capability to capture multi-temporal features of the time series, thus enabling modeling of non-stationarities. Also, because the RNNs use short-sequence LSTMs and are arranged in parallel, the computation time is substantially reduced to the sub-millisecond range. Here, the procedure to select the inputs of each RNN is altered to provide multi-step-ahead prediction capabilities.

Fig. 1(a) depicts the proposed procedure for extracting individual features in the source domain. At each discrete time step k, an RNN maps the input space $\mathbf{x}_k = \{x_{k-d\tau}, x_{k-(d-1)\tau}, \cdots, x_k\}$ to the next discrete value $x_{k+\tau}$, where τ is the time delay and d the embedding length. The number of extracted features is taken as the number of principal components used in representing at least 90% of the source domain. For each RNNs, variables τ and d are selected based on the embedding theorem to represent the essential dynamics of the associated principal components using the mutual information (MI) [7] and false nearest neighbors (FNN) [8] tests.

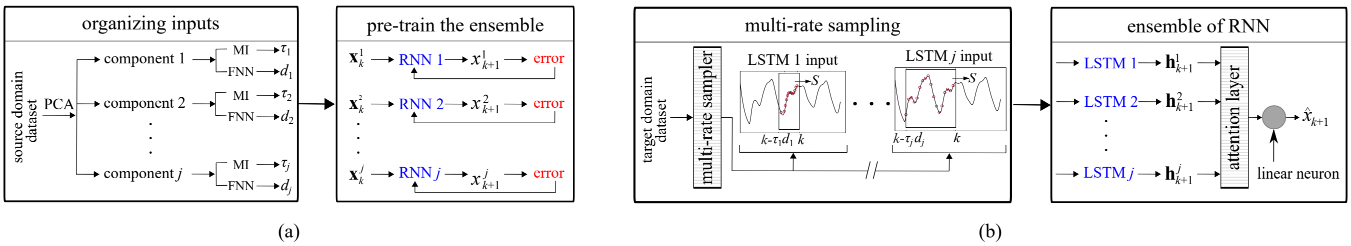

Figure 1: Proposed algorithm: (a) source domain training of the individual RNNs; (b) target domain real-time prediction architecture.

Fig. 1(b) depicts the algorithm for real-time one-step prediction in the target domain. The LSTM cells trained in the source domain are transferred to the target domain and run in parallel, each sampling the time series at different rates as data sequentially becomes available. A multi-resolution sampler at time step k extracts $\mathbf{x}_k^i$ for the i^{th} LSTM. Note that data is organized such that the target prediction value for all of the LSTMs is x_{k+1}. The features extracted in the LSTM layers are linearly scaled in an attention layer using a linear neuron. The squared error of the prediction is back-propagated to the network to update weights. Multi-step-ahead prediction is conducted by iterating the algorithm.

3. Simulations on Drop Tower Data

The proposed algorithm was validated using an experimental high-rate dynamic dataset obtained from an accelerated drop tower test [4]. Briefly, the setup, illustrated in Fig. 2(a), consists of an electronics package with four circuit boards mounted in a canister on an accelerated drop tower. At each time step k, four accelerometers measure the vibration of the boards sampled at 1 MHz. In this study, a single time series from accelerometer TS_1 is used as the source domain, and five different time series from accelerometer TS_2 produced from five different tests are used for target domain prediction.

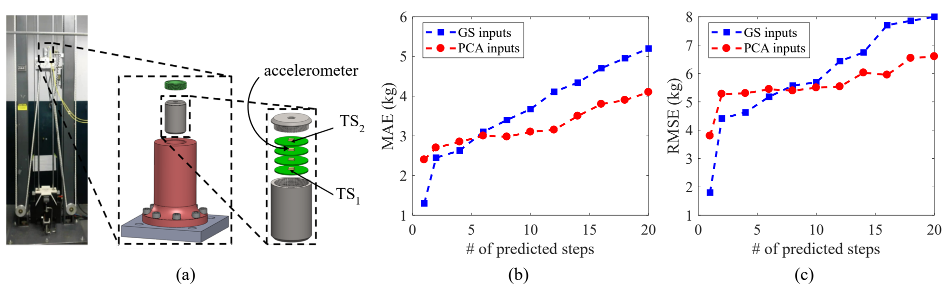

Figure 2: (a) Drop tower experiment setup; and prediction performance metrics MAE (b) and RMSE (c).

A total of 5 RNNs are used. To investigate the performance of the proposed method ('PCA'), a comparison is made with the case where the input parameters were selected through a grid search (GS) for one step-ahead prediction only, as done in [5]. Prediction performance was assessed over the range of 1 to 20 steps-ahead using the mean absolute errors (MAE) and root mean squared-error (RMSE) metrics. Results are plotted in Figs. 2(b-c). As expected, GS over-performed PCA over small prediction ranges. However, PCA shows more stable performance over the larger prediction horizon, yielding better performance after approximately 5 steps ahead, attributable to the extracted features enabling modeling of multi-resolution dynamics. A typical prediction time history is presented in Fig. 3 for 14 steps ahead, where to allow visual interpretation of results the algorithm is adapted after each 14 steps of prediction. Note that 1000 time steps is equivalent to 1 ms. A flat section indicates a naive prediction where the algorithm reports the previously predicted value as the current prediction. At the beginning of the prediction, both methods exhibit a naive behavior, but the PCA quickly improves its predictive performance as observable in the chaotic event around 500 time steps and after the event passed 600 time steps.

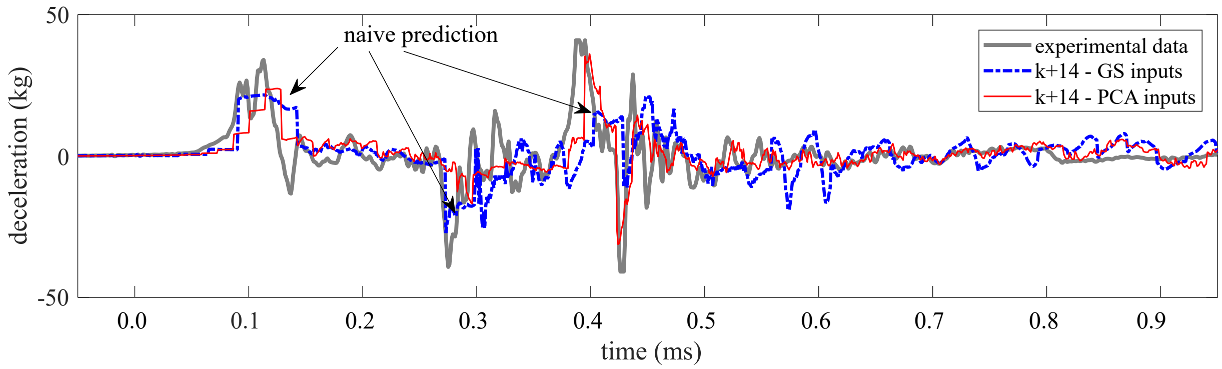

Figure 3: Comparison of prediction performance for 14 steps ahead.

4. Conclusion

In this paper, a new method for selecting the input space for an ensemble of RNNs was proposed, with the objective of enabling multi step-ahead prediction for high-rate systems. The selection was conducted based on the embedding theorem conducted on principal components representing the dynamics of the source domain. The performance of the proposed method was simulated on a set of experimental data and compared to a grid search method of organizing inputs. Results showed that the proposed method outperformed the grid search method for long prediction horizons.

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