Temporal information embedding neural network for structural seismic response prediction

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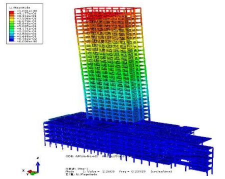
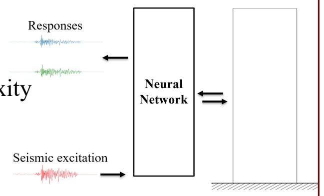
Background



Neural networks have been used to predict the response of structures on seismic excitation due to their excellent fitting ability. However, there are still several difficulties with predicting nonlinear response:

- Efficiently train accurate models using limited ground motion data.
- Overfitting caused by the complexity of models and limited data.
- Lack of utilization of numerical relationships between time steps.



A novel temporal information embedding network utilized specified feature generators and feature information embedding is proposed. The temporal information embedding network:

- **Not reliant on additional physical information**.
- **Learn distinct feature spaces and facilitates mutual correction between features**.

Concept: information embedding

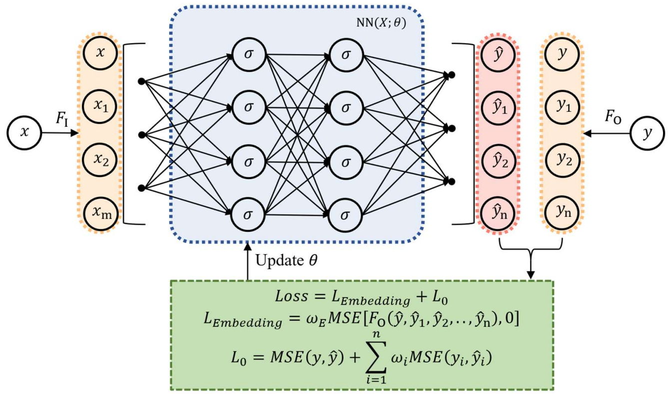


Figure 1 The concept of information embedding neural networks.

$Y = NN(X;\theta)$ is a neural network with X and Y as the input and output with the network parameters θ. The features are generated from original input data x and y using specific feature generators F_I and F_O. Where $F_I(x, x_1, x_2, \dots, x_m) = 0$, $F_O(y, y_1, y_2, \dots, y_n) = 0$. The embedding loss $L_{Embedding}$ is calculated according to the feature generator F_O. **The loss function $Loss$ used to update the parameters θ is obtained by weighting data residual L_O and embedding loss $L_{Embedding}$**

Concept implementation: Taylor's Formula embedding networks

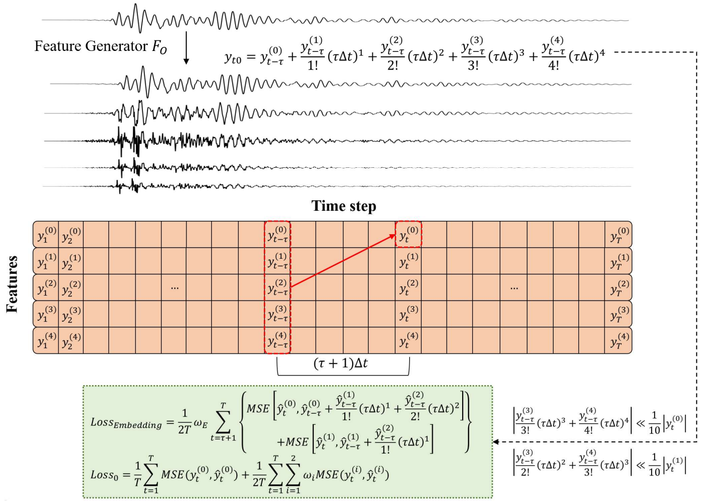


Figure 2 Taylor's Formula embedding neural network.

The feature generators F_I and F_O based on the Taylor expansion calculate the first 5 order derivatives of all sequences at Δt=0.1. It should be noted that the 0-th order derivative should be equal to the values of the original data.

$L_{Embedding}$ embeds Taylor's Formula by calculating **the bias between the data at the $(t-\tau)$ time step and the t time step**.

The first 3 order derivatives of output data are extracted as the embedding loss to avoid heavy calculations of the loss function.

Experimental Results

Model	Test loss		Time Spent	Pearson correlation coefficient
	MSE	MAE		
Basic Model	3.51E-3	3.45E-2	12.65 min	0.936
Temporal embedding Model	8.33E-4	1.49E-2	13.31 min	0.992

Table 1 Model performances of the models.

The performance indicators of the benchmark model and the temporal information embedding model were calculated based on 20 independent experiments. It is calculated that the MSE test error is improved by **76.27%** and the MAE test error is improved by **56.78%** after 10,000 epochs

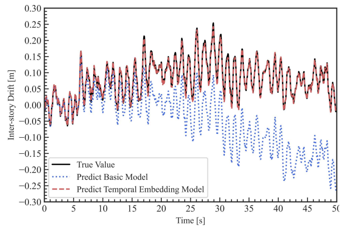


Figure 3 A seismic response comparison.

Experimental Results

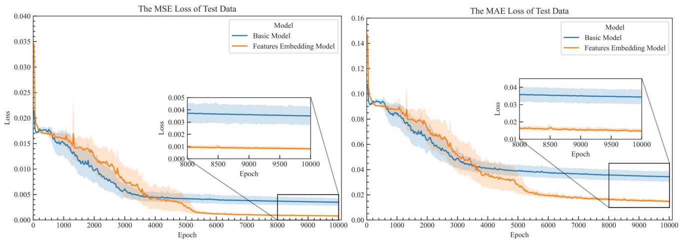


Figure 4 MSE loss and MAE loss of testing data.

The loss-epoch error bands are plotted at the 95% confidence level for the benchmark model and the temporal information embedding model.

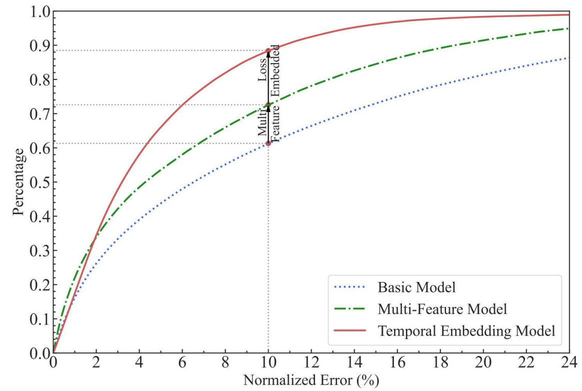


Figure 5 Cumulative distribution function of normalized error.

The multi-feature model improves 11.3% over the benchmark model within 10% of the cumulative distribution of normalization error, while the temporal information embedding model improves **27.3%**.

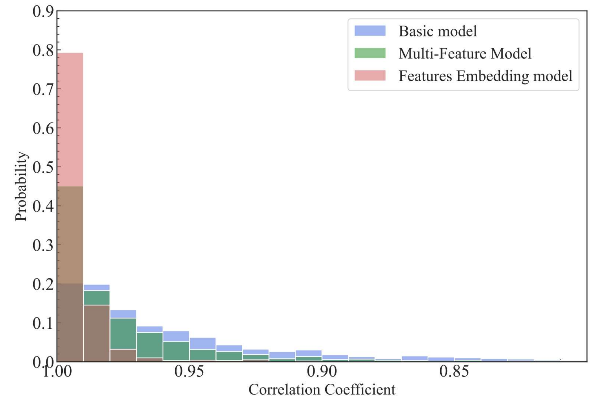


Figure 6 Pearson correlation coefficient distribution .