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FDTD Data Extrapolation Using Multilayer Perceptron (MLP)

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Abstract

This work compares MLP with the Matrix Pencil Method, a linear eigenanalysis-based extrapolator, in terms of their effectiveness in Finite Difference Time Domain (FDTD) data extrapolation. Matrix Pencil Method considers the signal as superposed complex exponentials while MLP considers each time step to be a nonlinear function of previous time steps.

Keywords

FDTD, neural networks, multilayer perceptron, EMC, data extrapolation, prediction, time series, complex exponentials

INTRODUCTION

FDTD simulations, which are widely used for simulating EMC characteristics of systems, are computationally very expensive. In order to boost the efficiency of the algorithm by stopping the simulation after a sufficient number of time steps and having an extrapolator predict the rest of the signal, we compare an MLP with a linear eigenanalysis predictor.

Looking from the frequency analytic point of view, all prediction attempts will have the restriction of confining the bandwidth of the frequency content of the predicted signal to that of the truncated signal that is used for reconstruction. So the prediction will lead to a loss in frequency information while shortening computational time unless the desired frequency range is already contained in the truncated signal.

FDTD IN ELECTROMAGNETIC COMPATIBILITY (EMC) SIMULATIONS

FDTD is a common method where impulse response of an electromagnetic system is simulated in time domain [3]. Output of the simulation is transformed to frequency domain, because measuring instruments work in this domain, and the behavior of the systems depends highly on frequency due to the resonant structures in systems.

As an example, shielding properties of enclosures can be simulated by their impulse response. Apparently, a perfect impulse is equivalent to flat white noise and shielding of an enclosure depends on the degree of attenuation it performs for different frequencies. The method is to induce an impulse from inside the enclosure and measure the attenuated signal outside.

If the geometry of the system to be tested is fully known, propagation of the impulse through the system can be simulated by FDTD through discretized Maxwell equations by computing the electric and magnetic fields, one following another, through two consecutive grids. As the system under test gets bigger, the simulation becomes computationally unaffordable. Namely, the shielding property of an enclosure might need to be simulated for as long as several weeks.

We know that FDTD simulations are not efficient but they are one of the best simulation tools at hand. The waste of resources in an FDTD simulation can be understood by considering the fact that two very different geometries having the same volume but very different complexity levels would require the same computational complexity as long as they have resonant structures. FDTD does not use the inherent symmetries in the systems, so the waste of resources is obvious.

Reducing the computational cost of such simulations would make more simulations possible, hence result in more creative and better designs. If we consider that most time domain simulations work in the same principle, any attempt for such an improvement may help improve the whole group.

An improvement model to FDTD is capturing the patterns inherent in the output time domain signal, using an extrapolator, from its partial results. One such extrapolator reported so far is a NN model. This work is the comparison of an FIR network with a linear ARMA extrapolator [2]. Another example is a study which considers extrapolation by Matrix Pencil Method assuming that the signal can be represented by superposed complex exponentials [4]. NN models perform well similar to their success in system identification [1].

APPLICATION

Current work is the comparison of a Multilayer Perceptron (MLP), a non-conventional nonlinear method, with that of the Matrix Pencil method, a linear method, in terms of their ability to predict rest of a truncated artificial signal. The artificial signal used is constructed by superposing a number of arbitrary decaying sinusoids which is known to be similar to FDTD signals in nature.

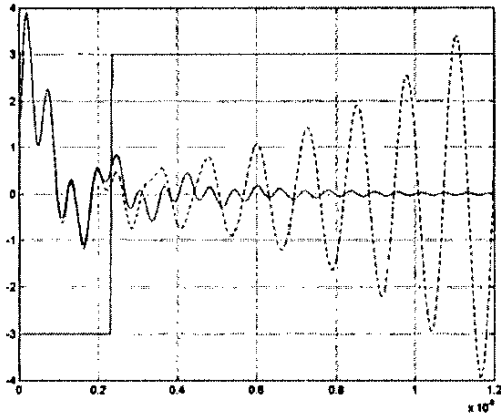


Figure 1: Extrapolation by Matrix Pencil Method where the signal is truncated at 16% of the total signal. Original signal is represented by solid and predicted signal is represented by dashed lines, vertical line shows the truncation point.

MLP is a feedforward neural network (NN) which is proven to be quite successful for its system identification and time series prediction ability [1].

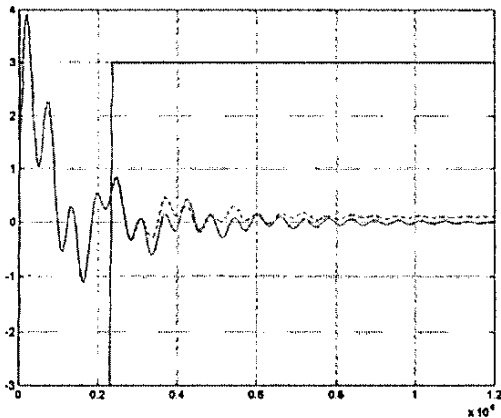


Figure 2: Extrapolation by Multilayer Perceptron (MLP) where the signal is truncated at 16% of the total signal. Original signal is represented by solid and predicted signal is represented by dashed lines, vertical line shows the truncation point.

The MLP architecture used in this study consists of an input layer of 6 neurons fed by the delayed time signal, one hidden layer of 8 neurons and a one-neuron output layer aimed to give the predicted next time step following the

window of delayed input time series. While the hidden layer neurons have tangential sigmoid transfer functions, the output layer has linear transfer function. The network is adaptively trained on the truncated signal by Levenberg Marquardt backpropagation. Then it starts constructing the rest of the signal by accumulating one step predictions.

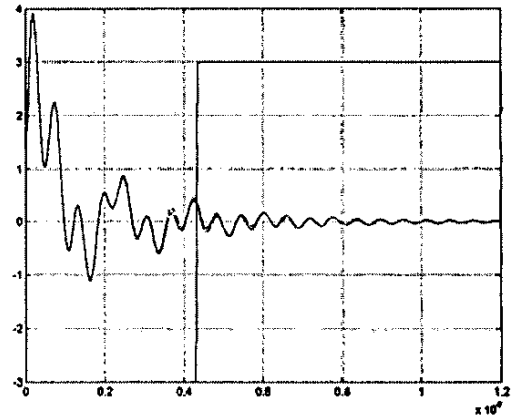


Figure 3: Extrapolation by Matrix Pencil Method where the signal is truncated at 32% of the total signal. Original signal is represented by solid and predicted signal is represented by dashed lines, vertical line shows the truncation point.

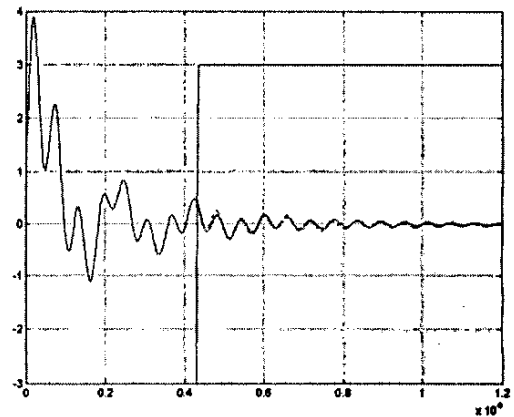


Figure 4: Extrapolation by Multilayer Perceptron (MLP) where the signal is truncated at 32% of the total signal. Original signal is represented by solid and predicted signal is represented by dashed lines, vertical line shows the truncation point.

Table 1. Comparison of prediction errors (% RMS)

Method\Truncation Point	16%	32%
MLP	4.02%	545.58%
Matrix Pencil Method	0.05%	1.12%

The Matrix Pencil Method is a method that allows system identification by means of the early time response of the system itself to an impulse [4]. The data obtained from this

response is fitted into two matrices and they are combined to form a generalized eigenvalue problem; the system is then approximated by a sum of complex exponentials with the real and imaginary parts provided, after some manipulations, by the eigenvalues previously found. The method is not adaptive by itself but in practice there are no limitations to the number of eigenvalues that can be extracted from the matrices.

An advantage of MLP over Matrix Pencil and other linear methods is its adaptivity. Moreover it doesn't need supervision. The MLP is capable of running parallel with the FDTD until either the training is saturated or until the length of the generated signal contains the desired frequency bandwidth.

RESULTS

Weight initialization is an important issue in MLP training. Different weight initializations can lead convergence to different optima of the training performance function. This might be overcome by offline training with similar signals. The extent to which offline training with different signals is successful should be examined in a following research.

The prediction results for two methods for two different truncation lengths can be seen in Figures 1 through 4. Figure 1 and 2 gives the results of extrapolation using the first 16% of the total signal by MLP and Matrix Pencil methods. Figure 3 and 4 gives the results of extrapolation using the first 32% of the total signal. It is clear that MLP is able to predict from a shorter truncated signal (16% of the total signal) which means more savings in terms of FDTD computation. For longer truncations (32% of the total signal)

both methods perform well but MLP is still more accurate. Percentage RMS prediction errors of the two methods are given in Table 1.

CONCLUSIONS

This overall work shows that MLP is a potentially convenient adaptive extrapolator for FDTD-type signals. Further research is proposed for making the input size and architecture of the MLP to be adaptive to different time step sensitivities and signal types.

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