Air Force/MIT Signal Enhancement for Magnetic Navigation Challenge Problem - A Machine Learning Based Filtering Approach

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We describe the machine learning method that we have developed for solving the “Signal Enhancement for Magnetic Navigation Challenge Problem”.

1 Multilayer Perceptron

A multilayer perceptron (MLP) is a feed forward artificial neural network composed of multiple layers of perceptron. It is a widely used machine learning model for regression problems. We have chosen it to be the core of our method because of its superior ability to extract the signal from noise and the relative ease to implement.

In our method, the input raw data are enhanced first by the Tolles-Lawson model and a low-pass filter, and are then fed into the an MLP with proper normalization. To reduce the variance in the machine output, we exploit an ensemble of MLPs with the same architecture, each trained with different random initial weights. The output filtered magnetic field signal is the average over the outputs of all the MLPs.

In the submitted scripts, we use an small ensemble of 12 MLPs. Each MLP has three hidden layers with 50, 30 and 10 neurons (from input to output), respectively. The activation function is $tanh$. The machine generates the filtered signal at the

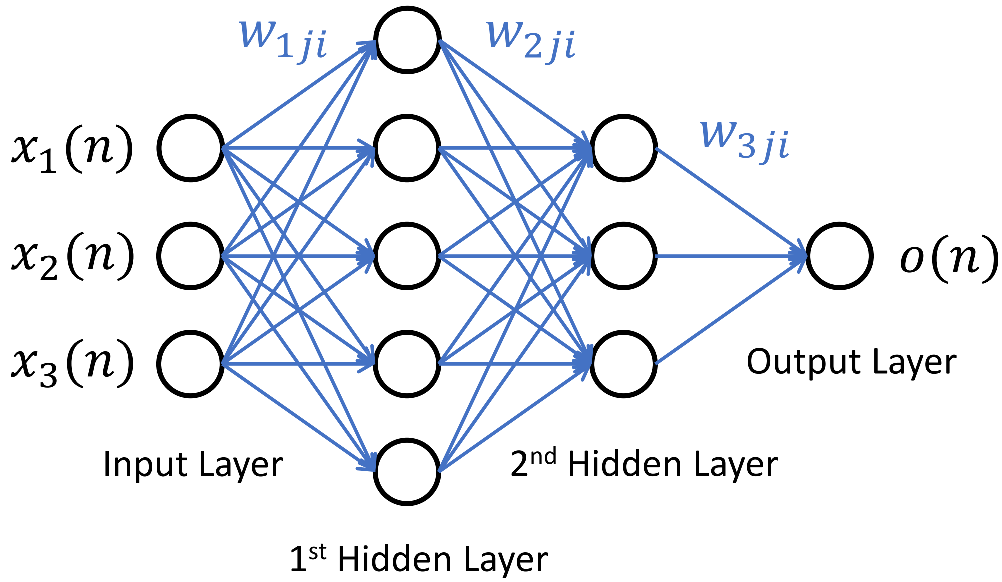

Figure 1: Illustration of the multilayer perceptron (MLP) in our method. The machine consists of an input layer, a number of hidden layers, and an output layer. The connection weights are determined through training.

output layer one step at a time. In particular, corresponding to each output data point, the input data consist of five time steps centered at the output time step. For example, for input data at $t = t_0 - 2, t_0 - 1, t_0, t_0 + 1$ and $t_0 + 2$, the machine generates an output data point at $t = t_0$.

2 Choice of Input Channels

Tests of the provided data suggest that the importance of the choice of the input data fields. Altogether, there are 55 different data fields provided for training. Because of the time constraint for this competition, it is infeasible to conduct brute-force tests of all the possible combinations of these data fields. We have adopted a recursive process in which we select one or two new input channels in each cycle through a loop over all possible channels, and we repeat this cycle with an increasing number of channels until the model performance saturates. Finally, we settle down with eleven data fields. They are:

- FLUXB_TOT
- FLUXB_X
- FLUXC_TOT
- FLUXC_Y
- FLUXD_Y
- FLUXD_Z
- UNCOMPMAG3 (with Tolles-Lawson correction)
- UNCOMPMAG3
- UNCOMPMAG4 (with Tolles-Lawson correction)
- UNCOMPMAG5 (with Tolles-Lawson correction)
- V_CABT

Both the data from sensor Mag 3 with or without Tolles-Lawson correction are used as input channels.

3 Results

We demonstrate the performance of our model with two representative data sets: those from line numbers 1003.02 and 1003.08. For each data set, the first four-fifth segment is used for training and the remaining one-fifth for validation. The trained MLP is then used to remove noise from the last one-fifth of the data under line number 1003.04. The validating and testing results are shown in Fig. 2. It can be seen that the signals extracted by the MLP agree with the true signals with small root-mean squared errors (RMSEs).

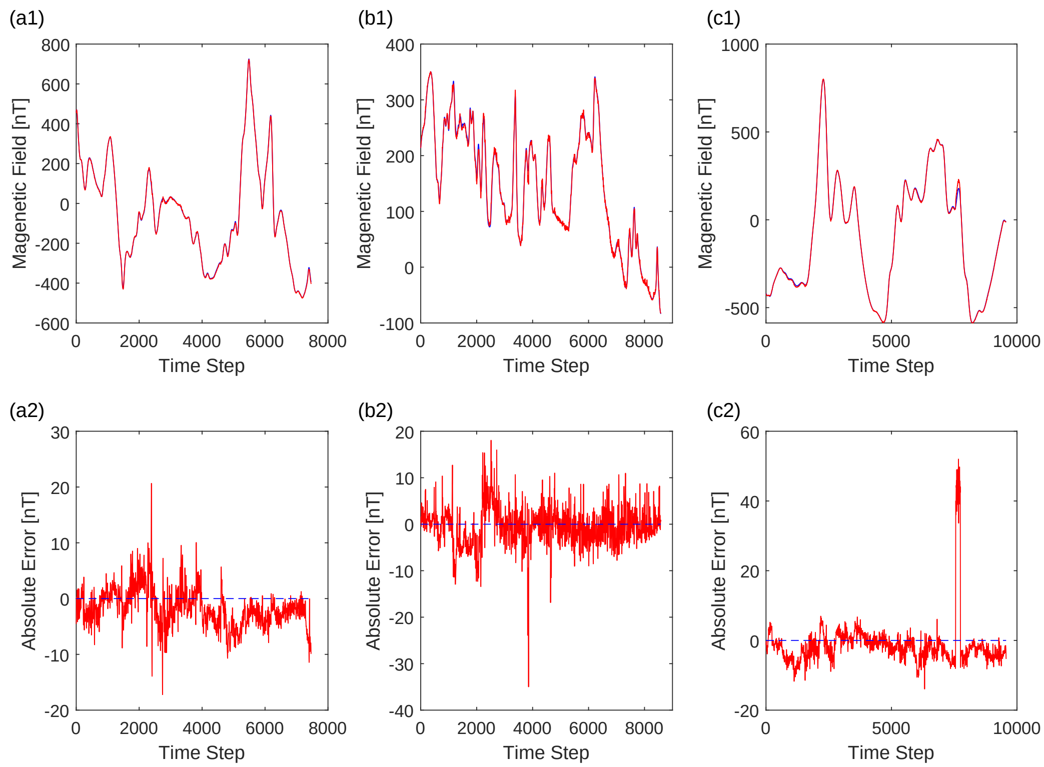

Figure 2: Performance of MLP in enhancing magnetic navigation signals. The red and blue curves represent the output of the neural network and the true signals, respectively. (a1,a2) Validating results for the data with line number 1003.02 ($RMSE = 3.8$). (b1,b2) Validating results for the data with line number 1003.08 ($RMSE = 4.2$). (c1,c2) Testing results for the data with line number 1003.04 ($RMSE = 7.2$).