INTRODUCTION

- Fine-scale RFID motion capture and localization systems are potential candidates for emerging applications such as robotic wayfaring, virtual reality, remote motion capture, and tracking;
- Hybrid schemes have the highest accuracy (5-400 cm) and largest range (hundreds of meters) by combining a variety of sources;
- We proposed a feed forward neural network estimator with input in time window to get rid of recurrent units, pre-known control vector, and the dynamic model. The designed estimator is added to measurement position velocity and acceleration states based on RFID-based states algorithm.

RFID L&T SYSTEM

- Tag that is mounted with an accelerometer, moves along with the position arm;
- Reader receives compacted (RSS + phase) from tag = (acceleration), and accelerometer data to obtain corresponding position, velocity and acceleration state data of the movement;

![RFID L&T System Diagram](image)

Fig. 1 Physical setup of the HIMR RFID L&T test system setup, which is moved along a 1-D track with pre-programmed coordinates

NEURAL NETWORK ESTIMATOR

- Input states in time window to a feedforward architecture makes the temporal domain spatial, making it capable of memorizing previous states as recurrent units.
- In a recurrent neural network, a sequence of vectors is processed by applying a recurrence formula onto states at this time step and previous states in memory. At timestep t, the state of the unit is
  \[
  h_t = \text{f}_{\text{nn}}(h_{t-1}, x_t) = \text{tanh}(W_h h_{t-1} + W_x x_t)
  \]
  \[
  y_t = \text{f}_{\text{output}}(h_t)
  \]

- \( h_t \) is the new state, \( h_{t-1} \) is the previous state, \( x_t \) is the input vector at time step t, \( f_{\text{nn}} \) is a function with parameters \( W_h \), \( W_x \) is the output of recurrent network.
- Constrain the length of recurrence to \( n \) (which is the batch size of input):
  \[
  h_t = \text{f}_{\text{nn}}(h_{t-1}, x_t) = \text{f}_{\text{nn}}(h_{t-n}, x_t)
  \]
  \[
  y_t = \text{f}_{\text{output}}(h_t)
  \]
- The relationship between \( n \) inputs \( x_t, \ldots, x_0 \) and output \( y_{t-n} \) of recurrent neural network can be approximated as:
  \[
  h_t = \text{f}_{\text{nn}}(\sum_{i=1}^{n} w_{i0} x_i + b_0)
  \]
  \[
  y_t = \text{f}_{\text{output}}(\sum_{i=1}^{m} w_{i0} h_i + b_0)
  \]  
- Which are the formulas of a general feedforward neural network. \( h_0 \) are the outputs of neurons in the hidden layer and \( y_t \) are the output of neurons in the output layer. \( f_{\text{nn}} \) is the identity function, \( f_{\text{output}} \) is \( \sigma \) function.
- In this way, weights from inputs \( x_1, x_2, \ldots, x_n \) to output \( y_t \) can be learned from a feedforward neural network.

ESTIMATOR STRUCTURE

- A 3-layer sequential neural network model composed of 10, 80, and 10 neurons;
- The time window of size 10, the processor will wait until 10 states arrive and then process continuously on the new state and 9 previous states all together;
- Activation functions in the hidden layers \( f_{\text{nn}} \) are linear and output layer \( f_{\text{output}} \) is \( \sigma \);
- 80% of the position states are used for training and 20% are for testing;
- The measurement position data are input at a batch size of 10. The model is trained with 200 epochs;
- Mean square error is minimized by adam optimizer during the training.

RESULTS

- Estimated routes is of much lower noise level compared to measurement
- RMS error before estimation is 31 mm after estimation is 14 mm for test states, which is a factor of 2 enhancement

<table>
<thead>
<tr>
<th>Measurement RMS Error</th>
<th>Estimation RMS Error on Test Position</th>
</tr>
</thead>
<tbody>
<tr>
<td>31 mm</td>
<td>14 mm</td>
</tr>
</tbody>
</table>

ESTIMATION RESULTS

- Fig. 3 Estimation Results for HIMR RFID Position Measurement
- Fig. 4 Estimation Results for Training and Testing Position Data