# A Feed Forward Neural Network for Determining a User's Location

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**ABSTRACT**

In this paper, I describe the implementation of a feed-forward neural network to allow a tabletop display system to determine a user's location based on how they hold their pen. The system utilizes the six-degrees-of-freedom from a Polhemus Fastrak magnetic tracking device as input to the neural network.

**Keywords**

Tabletop display, neural network, magnetic tracker, machine learning, context awareness

**INTRODUCTION**

Knowledge of a user's location relative to the table would prove useful to tabletop system developers. With this information, the system could adapt to movement of the user around the table and respond differently when many users attempt to use the same surface from different sides. Interaction with the tabletop display would be more seamless if this information was determined without the user's explicit input. That is, it would be useful if the system could somehow divine this information from the user whenever they interact with the tabletop display.

We have developed a system that utilizes the six-degrees-of-freedom (6DOF) supplied by a Polhemus Fastrak stylus input device to ascertain the location of a user. Our system uses this information as input to a feed-forward neural network that has been trained using backpropagation.

**WHY A NEURAL NETWORK?**

Many alternatives to the neural network were considered. We believe that a neural network was the most appropriate strategy to achieve the most accurate results.

**Heuristics vs. Machine-Learning**

One way to use the 6DOF to determine the location of a user would be to specify heuristic rules. For example, a rule could be "if the azimuth angle of the stylus is between 0° and 90°, then the user is at the SOUTH side of the table". This strategy could potentially locate a user with a high degree of accuracy, however these rules require the programmer to make many assumptions about how users operate a stylus device.

On the other hand, machine-learning algorithms use stochastic methods to devise a strategy for determining the user's location. In general, machine-learning algorithms require a set of training instances. Each training instance has both a given input and its corresponding output. In our case, the given input is the 6DOF of the stylus input device and the output is one of the four sides of the table. With this training corpus, a training algorithm is run to determine some rule or set of rules that will produce the desired output when given some input from the training corpus. These rules can then be used to determine the output for an arbitrary input.

We chose to use a machine-learning algorithm because it requires no assumptions. Also, the rules that it would determine are likely to be more precise than a heuristic "guess".

**Other Machine-Learning Algorithms**

There are a plethora of machine-learning algorithms from which to choose. Some other algorithms that were considered include the One-Rule strategy and the Naïve Bayes method. The One-Rule strategy simply determines the best rule to use to determine the side of the table. For instance, it might decide that only the azimuth angle is important in determining the side of the table and then classify the side based only on this attribute. The Naïve Bayes method uses a simple statistical model to determine the side of the table. That is, it calculates the probability that the user is at a particular side for each side of the table and returns the side with the highest probability.

We chose to use a neural network instead of these other strategies because we believed that it would be more accurate at predicting the side of the table. The One-Rule algorithm is a much simpler algorithm and ignores a lot of information that may prove useful in determining the side of the table. The Naïve Bayes method is perhaps suitable, however, it makes use of much simpler statistical theory than does the neural network.

## SYSTEM

For input to this network, we used information gathered from the 6DOF Polhemus Fastrak magnetic tracking device. To eliminate magnetic interference, a wooden table was used. Furthermore, to correct for unavoidable magnetic fields within the area of use of the device, it was necessary to calibrate the input using a fourth degree polynomial fit algorithm [1].

## IMPLEMENTATION

Here we describe the details of the specific feed-forward network that we used to determine the location of a user.

### Description of the Network

The neural network that we implemented has three layers. The input layer has one node for each of the 6DOF, the output layer has one node for each of the four sides of the table and the hidden layer has five nodes. The nodes of the network are fully connected between each of the layers (see Figure 1).

### Using the Network

The network functions by propagating the activation from the input layer towards the output layer. First, the activation of each hidden node is calculated as a weighted sum of the activation of its adjacent nodes in the input layer. That is, the activation of the $j^{th}$ node in the hidden layer is determined by the following equation:

$$a_j = \sum_{i=1}^{6} w_{ij} a_i$$

where $a_1, \ldots, a_6$ are the activation levels of the six input nodes. Similarly, the activation of nodes in the output layer is calculated by a weighted sum of activation of adjacent nodes in the hidden layer.

### Training the Network

Before the network can be used to determine the side of the table with any degree of accuracy, it must be trained. Training is performed using the backpropagation [2] algorithm. That is, for each instance in the training corpus, the input is used as activation for the input layer and is propagated to the output layer. The received output is then compared to the desired output and an error value is calculated for each node in the output layer. The weights on edges going into the output layer are adjusted by a small amount relative to the error value. This error is propagated backwards through the network to correct edge weights at all levels. For our particular network, a learning rate of 0.5 and a momentum of 0.4 were used. The training corpus was passed through the network 100 times.

## CONCLUSION

The feed forward network described in this paper is capable of determining the side at which a user is sitting at a tabletop display based on how they hold their stylus input device. This feat can be accomplished using a feed forward neural network data mining technique. Although other techniques may prove accurate at the same task, the neural network seems to be a suitable and sufficiently accurate choice.

The use of a neural network in this manner makes it possible to automatically detect the location of a user. Thus the computer can more easily adapt to changes in the user's position as well as to multiple users in different locations. The existence of this technology opens the door for programmers to create tabletop display environments that can better anticipate the needs of its users.

## REFERENCES


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