

Real-time Gesture Mapping in Pd Environment using Neural Networks

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ABSTRACT

In this paper, we describe an adaptive approach to gesture mapping for musical applications which serves as a mapping system for music instrument design. A neural network approach is chosen for this goal and all the required interfaces and abstractions are developed and demonstrated in the Pure Data environment. In this paper, we will focus on neural network

networks designed in these simulators and produces text files that consequently serves as input for the Neural Network abstractions in Pure Data real-time music programming environment [5]. Our final goal is to implement a neural network training environment in Pure Data itself that handles several architectures and network schemes useful for instrumental and gestural system design.

During this research, several network architectures and training schemes were evaluated and those suitable for general musical applications were implemented for further use. We experimented with two general architectures: Static-networks and Dynamic-networks. In a static network, we map the data without any use of time-delay for recognition and in dynamic application we use time-delay that introduces a notion of memory in a pattern recognition problem and allows gesture mapping and control.

In the second stage, data acquisition is done using series of sensors that describe gestures. A sensor interface routes this data to a real-time software environment containing a trained neural network. Finally the neural network produces the desired parameters for event generation and continuous control of a musical process or application. A well-trained neural network system in general, would generalize its knowledge and respond to unseen gestures appropriate to defined preferences.

The interest of the adaptable mapping lies in the ability to use any input device for mapping. For the sake of this research, data acquisition is done using La kitchen’s sensors and the “Toaster” or the wireless “Kroonde” interfaces [3] (see Figure1). These interfaces provide the gesture data to a real-time musical application using the OpenSoundControl protocol [4]. Preprocessing operations designed with the interface and sensors, prepare the desired inputs for the trained network. Sensors and interfaces designed in La kitchen allow a time resolution input of 5ms (equivalent of 200Hz) with 10-bit precision for “Kroonde” and 16-bit precision for “Toaster” which would allow high-resolution control over the events.

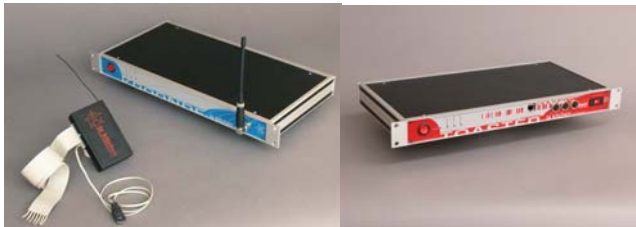


Figure 1. Kroonde and Toaster, high-resolution real-time sensor interfaces.

For the real-time musical environment, Pure Data [5] is chosen for its availability, open-source license and its active community. Data acquisition patches were already available for the mentioned sensors and interfaces along with some preprocessing tools in Pure Data developed at La kitchen. Neural network abstractions are created in Pure Data which take a trained network and perform the network operations. For their design, we had the following constraints in mind:

- x High-level and easy interface
- x General network implementation that minimizes the sophistication of huge networks
- x Real-time performance

4. NEURAL NETWORK REALIZATION IN PURE DATA

A general neuron is presented in Figure 2. A designed network consists of a series of additions and multiplications along with a transfer function. Each neuron’s operation can be considered as vector operations.

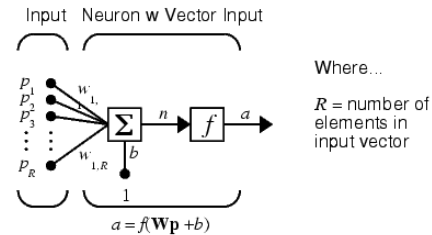


Figure 2. A neuron model in a neural network

A neural network is made up of layers, each of which contains several neurons. With the above model, problems arise when constructing more complicated networks that demand a large number of neurons. To solve this sophistication, we consider each layer as a matrix operation as shown in Figure 3. In this approach, the number of neurons used depends on the size of the input vector and weight matrix and all operations including the transfer function would be on matrices instead of numbers. Most matrix operations for this purpose are available through Pure Data’s Zexy library.

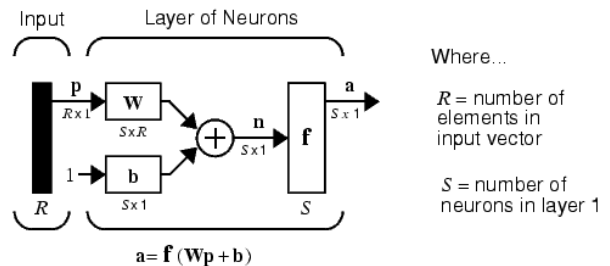


Figure 3. Matrix representation of a layer in a neural network

Figure 4 shows a Pd realization of a layer in neural network. Each layer, despite the number of neurons will be represented by one abstraction and reduces the complexity of network representation. The left inlet accepts the input arranged as a matrix and other inlets would be the trained network parameters which are: layer’s weight matrix (equivalent of **w** in Figure 5), layer’s bias vector (equivalent of **b** in Figure 5) and the transfer function. These trained parameters are loaded only once into the patch. The transfer function is selected by sending a symbol to the inlet which can be either a log-sigmoid or tan-sigmoid functions. Due high-level representation of network parameters, more transfer functions can be defined by the interested user. In our applications so far, we have not encountered any need for others. The two mentioned transfer functions output data in a range of [0,1] and [-1,+1] respectively which is useful to know for designing the network.

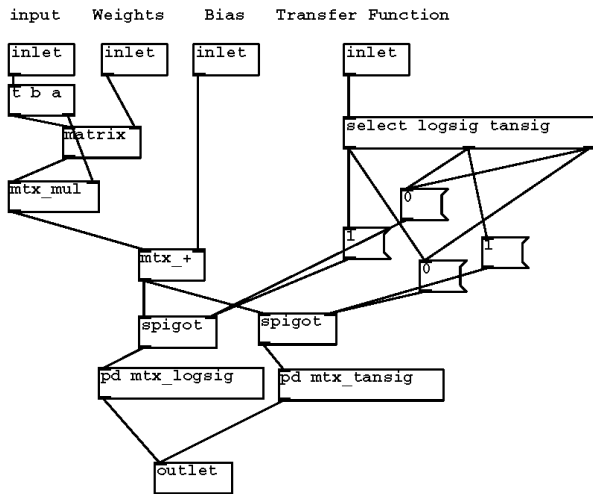


Figure 4. Pd abstraction of a layer of a neural network

For time-delay considerations- to be elaborated in the following sections- we prepare the inputs of a neural network using down sampling and constructing delay lines.

Using the above abstraction, we have constructed a time-delay feedforward neural network which can be used for mapping and gestural recognition systems. There is only one mathematical function which is written as an external for PD. The high-level aspect of this realization allows easy modification of the architecture and implementation of other architectures using the same concept. Figure 5 shows the details of a two layer neural network which will be used as a single abstraction in a mapping system patch.

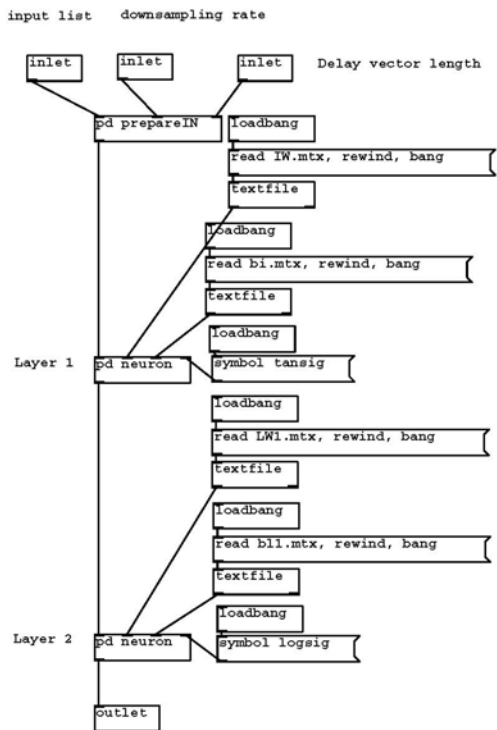


Figure 5. Details of a two-layer network patch

5. TRAINING THE NEURAL NETWORK

Network design and training is the first step towards constructing a network for real-time mapping. For this, the user will need some predetermined input samples, their targets and a defined architecture to start the training.

The training session of a neural network does not require an expertise to realize the network. An empiric approach with trials and errors would eventually make the network converge to the desired behavior. However, a clever choice of network architecture and parameters would save a lot of time in realizing the network.

In our experience, for most musical applications, a maximum of three hidden layer seems to suffice. While use of excessive neurons makes the network converge more rapidly, it degrades the generalization in most applications. There is no law determining the number of neurons needed; this factor is realized by a heuristic approach towards the design of neural networks.

There are numerous learning methods available in the neural network literature. For sensor mapping applications, batch training suffices for convergence. However due to high non-linearity of sensors, the most convenient method does not necessarily converge. We have found that for most sensor mapping applications, the Reduced-Memory-Levenberque-Marquardt algorithm [6] converges with acceptable generalization.

After the training is done and results are satisfactory, network weights and parameters are automatically prepared as Pd MTX files to be used in the real-time application.

6. REAL-TIME APPLICATION

At this point, we will examine the neural network mapping for two different applications: a static network which would map a sensor network to a simple spherical coordinate and a dynamic network for pattern recognition of a circular movement using a network of sensors.

6.1 Static Networks

Two experiments were performed: the first with two magnetic sensors on the palm, and the second with one flexure sensor and one magnetic sensor on the ankle and near the shoulder respectively. The goal was to map these input values to Cartesian and Spherical coordinates. A total of 25 points were used as samples for network training.

Satisfactory behavior is observed for a two-layer network architecture with a goal of 0.01 and network parameters are exported to Pd MTX files.

The network realization using the abstractions discussed in section 4 is shown in Figure 6. Sensor inputs are routed using the OSC protocol and from the wireless Kroonde interface. The sensor data is preprocessed, calibrated and fed into the network. As is seen in the figure, only one neural network abstraction is presented in the patch which takes care of all the mapping. All the rest are data acquisitions and preprocessing.

Real-time performance is achieved using 200Hz data entrance and the final layer output would correspond to the desired behavior and can be used for further control.

