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Analog Neural Circuit and Hardware Design of Deep Learning Model

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Abstract

In the neural network field, many application models have been proposed. Previous analog neural network models were composed of the operational amplifier and fixed resistance. It is difficult to change the connecting weight of a network. In this study, we used analog electronic multiple and sample hold circuits. The connecting weights describe the input voltage. It is easy to change the connection coefficient. This model works only on analog electronic circuits. It can finish the learning process in a very short time and this model will enable more flexible learning. However, the structure of this model includes only one input and one output network. We improved the number of unit and network layers. Moreover, we suggest the possibility of the realization the hardware implementation of the deep learning model.

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Keywords: electronic circuit, neural network, multiple circuit omponent

1. Introduction

We propose the dynamic learning of the neural network by analog electronic circuits. This model will develop a new signal device with the analog neural electronic circuit. One of the targets of this research is the modelling of biomedical neural function. In the field of neural network, many application models have been proposed. And there are many hardware models that have been realized. These analog neural network models were composed of the operational amplifier and fixed resistance. It is difficult to change the connection coefficient. The analog neural network expresses the voltage, current or charge by a continuous quantity. The main merit is it can construct a continuous time system as well as a discrete time system by the clock operation. Obviously, the operation of the actual neuron cell utilizes analog. It is suitable to use an analog method for imitating the operation of an actual

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neuron cell. Many artificial neural networks LSI were designed by the analog method. Many processing units can be installed on a single-chip, because each unit can be achieved with a small number of elements, addition, multiplication, and the nonlinear transformation. And it is possible to operate using the super parallel calculation. As a result, the high-speed offers an advantage compared to the digital neural network method [1][2]. In the pure analog circuit, the main problem is the achievement of an analog memory; how to memorize analog quantity [3].This problem has not been solved yet. The DRAM method memorizes in the capacitor as temporary memory, because it can be achieved in the general-purpose CMOS process [4]. However, when the data value keeps for a long term, digital memory will also be needed. In this case, D/A and A/D conversion causes an overhead problem. Other memorizing methods are the floatage gate type device, ferroelectric memory (FeRAM) and magnetic substance memories (MRAM) [5][6].

1.1. Pulsed Neural Network

Another hardware neural network model has been proposed. It uses a pulsed neural network. Especially, when processing time series data, the pulsed neural network model has good advantages. In particular, this network can keep the connecting weights after the learning process [7]. Moreover, the reason the learning circuit uses the capacitor is that it takes a long time to work the circuits. In general, the pulse interval of the pulsed neural network is about 10μS. The pulsed neuron model represents the output value by the probability of neuron fires. For example, if the neuron is fired 50 times in a 100 pulse interval, the output value is 0.5 at this time. To represent the analog quantity using the Pulsed Neuron Model, there needs to be about 100 pulses. Thus, about 1mS is needed to represent the output analog signal on a pulsed neuron model.

In this study, we used the multiple circuits. The connecting weights describe the input voltage. It is easy to change the connection coefficient. This model works only on analog electronic circuits. It can finish the learning process in a very short time and this model will allow for more flexible learning. Recently, many researchers have focused on the semiconductor integration industry. Especially, low electrical power, low price, and large scale models are important. The neural network model explains the biomedical neural system. Neural network has flexible learning ability. Many researchers simulated the structure of the biomedical brain neuron using an electronic circuit and software.

1.2. Overview

The results of the neural network research provide feedback to the neuro science fields. These research fields have been widely developed in recently. The learning ability of a neural network is similar to the human mechanism. As a result, it is possible to make a better information processing system, matching both advantages of the computer model and biomedical brain model. The structure of the neural network usually consists of three layers, the input layer, intermediate layer and output layer. Each layer is composed of the connecting weight and unit. A neural network is composed of those three layers by combining the neuron structures [8][9].

In the field of neural network, many application methods and hardware models have been proposed. A neuro chip and an artificial retina chip are developed to comprise the neural network model and simulate the biomedical vision system. In this research, we are adding the circuit of the operational amplifier. The connecting weight shows the input voltage of adding circuits. In the previous hardware models of neural net-work, changing connected weights was difficult, because these models used the resistance elements as the connecting weights. Moreover, the model which used the capacitor as the connecting weights was proposed. However, it is difficult to adjust the connecting weights. In the present study, we proposed a neural network using analog multiple circuits. The connecting weights are shown as a voltage of multiple circuits. The connecting weights can be changed easily. The learning process will be quicker. At first we made a neural network by computer program and neural circuit by SPICE simulation. SPICE means the electric circuit simulator as shown in the next chapter. Next we measured the behaviour confirmation of the computer calculation and SPICE simulation. We compared both output results and confirmed some extent of EX-OR behaviour [10].

2. SPICE

In this research, we used the electric circuit simulator SPICE. Electric circuit simulator (SPICE) is the abbreviation of Simulation Program with Integrated Circle Emphasis. It can reproduce the analog operation of an electrical circuit and the electric circuit. After this, the circuit drawn by CAD, set the input voltage. SPICE has the function of AC, DC and transient analysis. At first, we made the differential amplifier circuits and Gilbert multipliers circuits. And we confirmed the range of voltage operated excellently. The neuron structure was composed of multiple circuits by an operational amplifier for multiplication function achievement, current mirror circuits to achieve nonlinear function and differential amplifier circuits. In the previous hardware model of neural network, we used the resistance element as a connecting weight. However, it is difficult to change the resistance value. In the neural connection, it calculates the product the input value and connecting weight. We used the multiple circuit as the connecting weight. Each two inputs of multiple circuits means an input value and connecting weight. The connecting weight shows the voltage value. It is easy to change the value in the learning stage of the neural network.

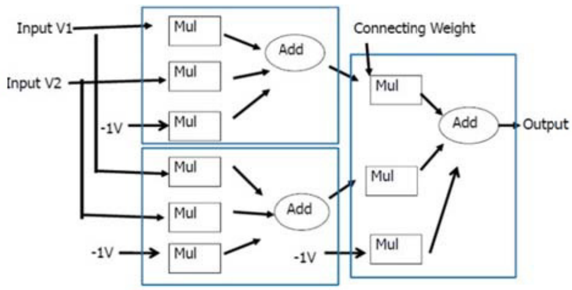

Fig. 1. The Architecture of Three-Layers Neural Circuits.

Fig. 2. Experimental Result of Three-Layers Neural Circuits.

3. Three Layers Neural Network

We constructed a three layer neural network, with an input layer, middle layer and an output layer. There are two input units, two middle units and one output unit. We combined the neural unit described in the preceding chapter. In Figure 1, we show the block diagram of a general neural network model. However it uses the multiple circuit for easy changing of the connecting weight. "Mul" means multiple circuits and "Add" means addition of circuits in Fig. 1. The experimental result is shown in Fig. 2. We confirmed when the range of the voltage is between -0.05V and 0.15V, this circuit operated normally. The linear graph is the output of the middle layer and the nonlinear graph is the output of the final layer in Fig. 2 [11]. In the middle layer, we achieved a good output signal. In the output layer, there was a little distortion signal. However, this will not present a significant problem on the neural network output.

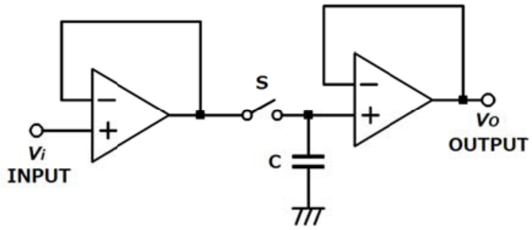

Fig. 3. Sample Hold Circuits.

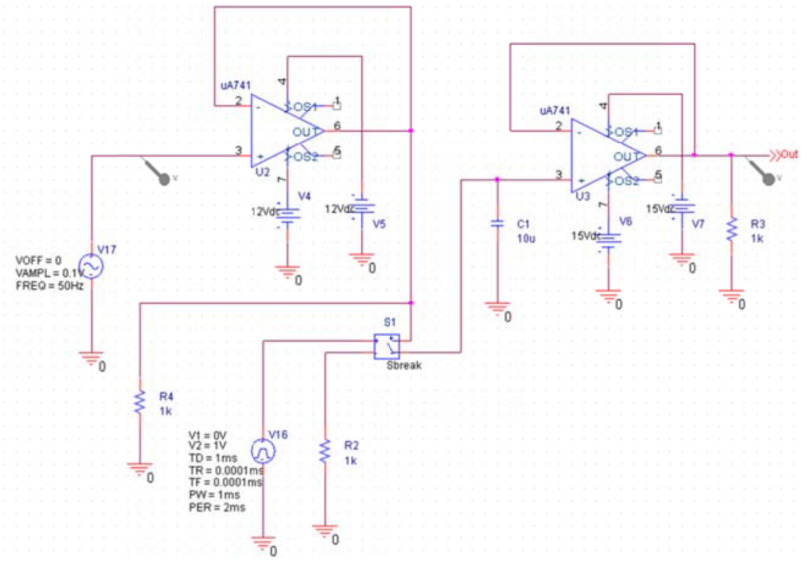

Fig. 4. Sample Hold Circuit by SPICE

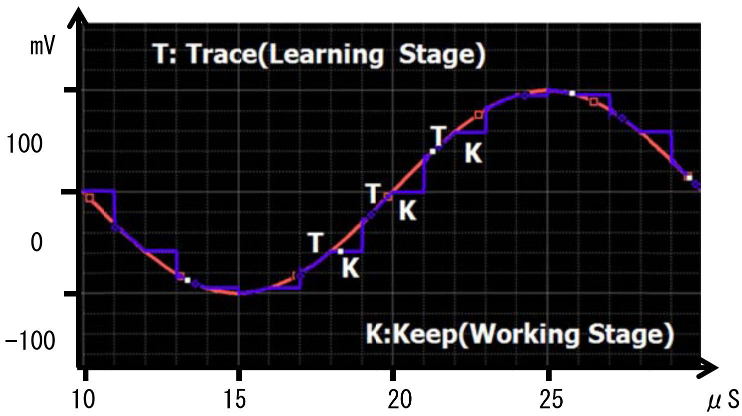

Fig. 5. Simulation Result of Sample Hold Circuit

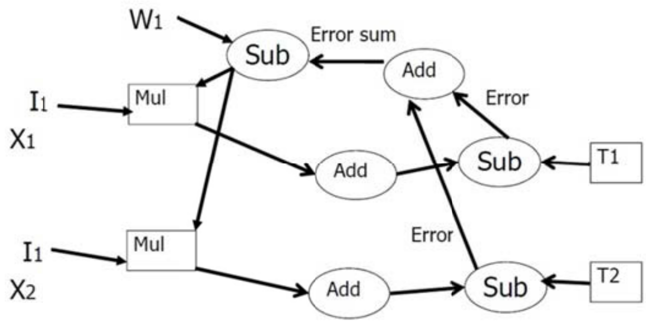

Fig. 6. The Circuit of Learning Stage.

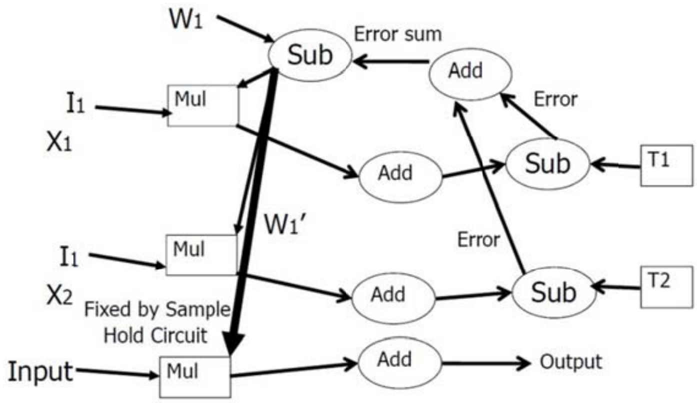

Fig. 7. The Circuit of Working Stage.

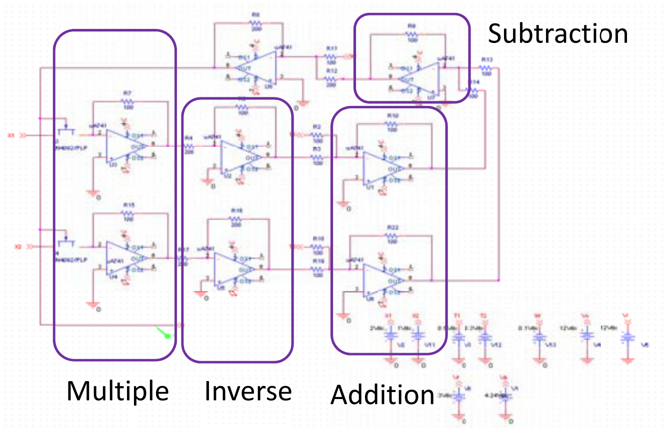

Fig. 8. The Learning Neural Circuit on Capture CAD by SPICE.

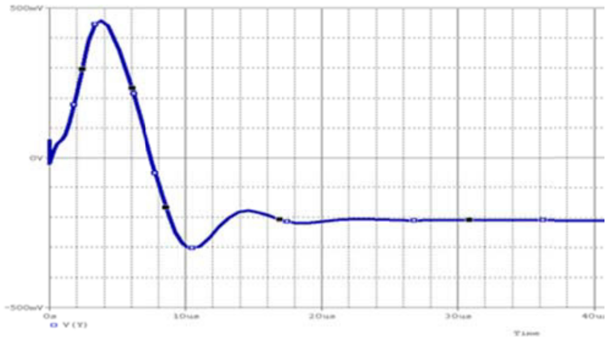

Fig. 9. The Simulation Result of Learning Experiment.

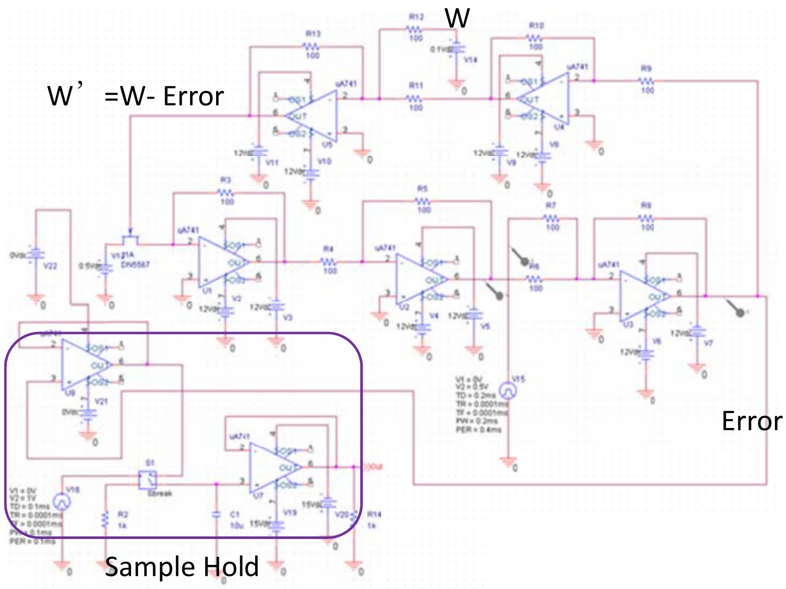

Fig. 10. Basic Neural Circuit with Sample Hold Circuits

4. Dynamical Learning Model

We used the analog neural network, explained in a previous chapter. In this chapter, we explain the dynamical learning model. This model can change the connecting weights by variable input voltage. This model has two stages, a learning stage and a working stage. In the learning stage, we used analog feedback circuits. We used a separate neural network of each teaching signal. Real-time learning is possible. However, in the learning stage, it is impossible to hold the connecting weights. We used the sample hold circuit to hold the connecting weights in the working stage. In the working stage, this network accepts input signal and outputs the answer, calculated by the connecting weights.

This circuit can perform periodical work, learning stage and working stage [12]. In Fig. 3, we show the Sample Hold Circuits. They can keep the output value for a brief time in the holding mode when the switch “S” is turn off. However, when the switch is turn on, this circuit situation is in “sampling mode”. In the sampling mode, it is the same value for the input signal and output signal. We constructed the Sample Hold Circuit by CAD and simulated by

SPICE. In Fig. 5, we show the simulation result of sample hold circuits. “T” means tracing the input signal. In this situation, the circuit condition is learning stage. “K” means keeping the signal in spite of changing the input signal. The circuit condition is working stage. This stage means the connecting weights keep the value for a brief time in the holding mode. In this situation, this neural network accepts the input value and calculates the output signal. We use a separate neural network for each teaching signal. Real-time learning is possible. We used the sample hold circuit in the working stage. It can hold the connection weights. In the working stage, this neural network is working. This circuit can make periodical work, learning mode and working mode.

In Fig. 6, we show the learning stage. “Mul” means multiple circuits, “Add” means additional circuits and “Sub” means subtraction circuits. In Fig. 7, we show the working stage of analog neural network. The void arrow line from the upper part to the lower part in Fig. 7 means fixed value of sample hold circuit. It can hold the connecting weight. There are two input lines, I_1 in Fig. 6 and Fig. 7. However, X_1 and X_2 are each learning pattern. These are simplification figures, showing the one input signal, one output signal and two kinds of learning patterns. In the base of our previous paper [13][14], we have the additional experiment. We stated each resistance or capacitor value on the Capture CAD by SPICE, in Fig. 8. This circuit is constructed by multiple, inverse, addition and subtraction circuits as in Fig. 8.

In Fig. 9, we show the result when the input signal is a square wave. We got the result, the learning time is about 20μs and convergence voltage is -200mv. After spending 20μs, the output value is constant. We assume that the working time is also 20μs. The learning cycle of this circuit is 25,000 times per second. The learning speed of this model is very high in spite of a very simple circuit using low cost elements. Repeating the learning mode and working mode, the circuits can realize flexible learning. We show the Basic Neural Circuit with Sample Hold Circuits in Fig. 10. When the Sample Hold Circuits is in keeping mode, this circuits’ outputs the fixed connecting weights.

On the other hand, the pulsed neural Network has an advantage. Particularly, this network can also keep the connecting weights after the learning process. However, it takes a long time for the learning process when many pulses are required. As the typical pulsed neuron model, about 1000 pulses were required for the learning process. However, our proposed model is constructed with a cheap electrical device. If we use the high quality analog electrical device, the learning speed will be improved more than the pulsed neuron model. In the result of this experiment the performance is low because of using general-purpose, inexpensive parts. The operating speed will be improved by using a high-performance element which has a good slew rate. However, this system is a simple circuit. The number of parts is few. The cost will not raise much even if good performance parts are used.

5. Deep Learning Model

Recently, a deep learning model has been proposed. Deep learning is a kind of algorithms in learning model. It attempts the high-level categorizing of data using multiple non-linear transformations and one method of machine learning. In the field of image recognition and speech recognition, the deep learning method has attracted the attention.

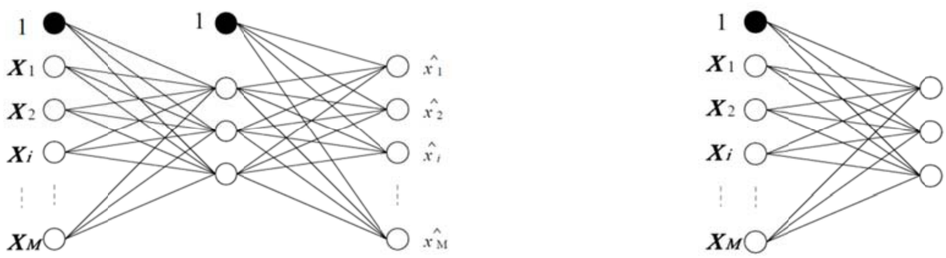

Fig. 11. Learning the Auto-encoder and Removing the Decoding Part of Stacked Auto-encoder

5.1. The stacked auto encoder

The stacked auto-encoder is one method of deep learning. This is the pre-learning method of large number layer network. How to construct the deep layer network is as follows. After the learning process of stacked auto-encoder is completed, remove the decoding part (output layer) of stacked auto-encoder and keep the coded portion (from the input layer to the intermediate layer). Thus we obtain the network which converts from input signal to compressed information representation. Moreover, we obtain more compressed internal representation, as the compressed representation input signal to apply the auto-encoder learning. Thus, we obtain a multi-layered hierarchical network, recursively repeated auto-encoder learning, and stacked the encoding part of the network. This constructed multilayer network is called stacked auto-encoder. In this way, after building a multi-layer network, to add the identified network using the output of the final layer, a new supervised learning method is proposed.

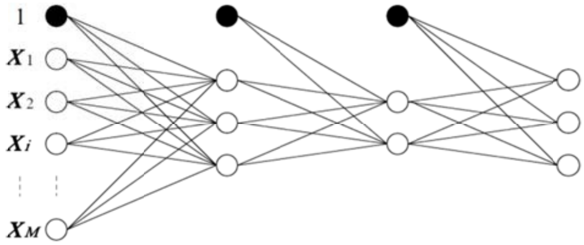

Fig. 12. The Compressed Internal Representation.

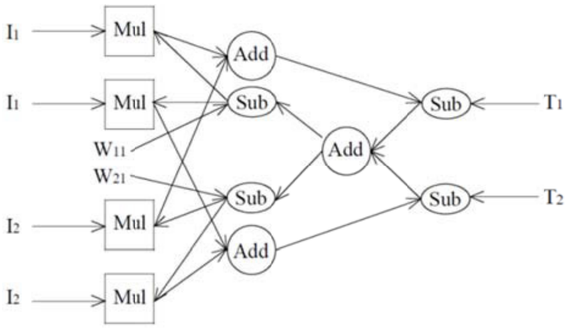

Fig. 13. The structure of 2-input, 1-output and 2-patterns analog neural network.

Stacked auto-encoder has been applied to the various subject as well as the DNN which is stacked the RBM. Recently, it became famous the learning experiment of feature extractor from a large amount of image. This network structure is nine layers with three superimposed sub-network such as convolution network. It was learned 10 million images as an input signal which are cut out from 10 million pieces of YouTube video. Each sub-network is made by unsupervised learning using the stacked auto-encoder method. As a result, it has been reported the neurons are formed which are respond specifically to various kinds of objects types such as a human face, cat face and drink bottles.[15] In the previous research, we described the dynamical neural network learning model. However, this model has only one input unit and one output unit. To realize the hardware deep learning model, we have to increase the number of units in each layer. Next, we constructed a 2 input, 1 output and 2 patterns neural model as in Fig. 13. I_1 and I_2 are input units. Two I_1 mean two inputs. T_1 and T_2 means two teaching signals. W_{11} and W_{12} are connecting weights. Fig. 14 means the structure of 2-input, 1-output and 4-patterns analog neural network. It means 4 input and 4 teaching signals of each pattern. Fig. 15 means the structure of 2-input, 2-output, 2-patterns and 3-layers analog neural network. Although this model needs many neural connections, the learning speed is very high. After learning, picking up each new connecting weights between input layer and middle layer. These connecting weights are used by the one layer of the deep learning model. We will pick up each output value of the middle layer. These output values of the middle layer uses as the input value of next repeat of auto-encoder learning. This model suggests the possibility of the realization of the hardware implementation of the deep learning model.

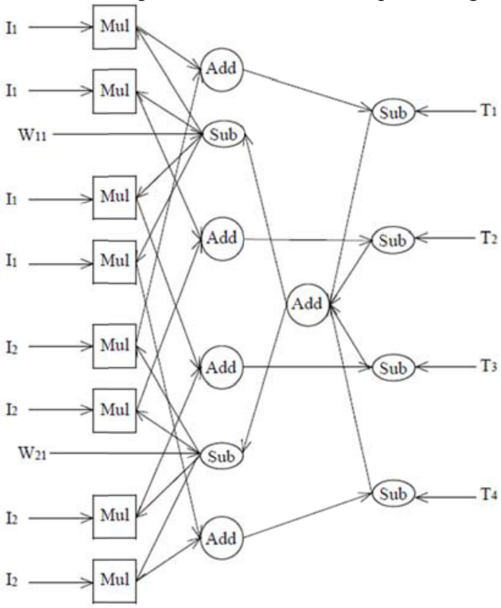

Fig. 14. The structure of 2-input, 1-output and 4-patterns analog neural network

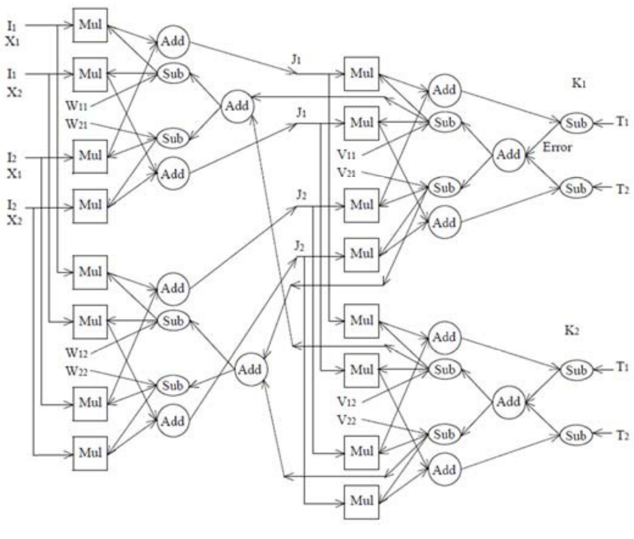

Fig. 15. The structure of 2-input, 2-output, 2-patterns and 3-layers analog neural network

6. Conclusion

We constructed a three layer neural network, two-input layers, two-middle layers and one output layer. We confirmed the operation of the three layer analog neural network with the multiplying circuit by SPICE simulation.

The connection weight can be changed by controlling the input voltage. This model has extremely high flexibility characteristics. When the analog neural network is operated, the synapse weight is especially important. It is how to give the synapse weight to this neural network. To solve this problem, it is necessary to apply the method of the back propagation rule that is a general learning rule for the multiple electronic circuits. This neural circuit model is possible the learning. The learning speed will be rapid. And dynamic learning will be realized. The method is calculating the difference between the output voltage and the teaching signal of the different circuits and the feedback of the difference value for changing connecting weights. The learning cycle of this circuit is 25,000 times per second. The learning speed of this model is very high in spite of a very simple circuit using low cost elements.

The learning time of this model is very short and the working time of this model is almost real-time. The pulsed neuron model represents the output value by the probability of neuron fires. To represent the analog quantity using the Pulsed Neuron Model, enough time for at least a few dozen pulses is needed. The output value of this model is the output voltage of this circuit. We don't need to convert the data; we can use the raw data from this model. This model allows for switching the working mode and learning mode. It is always necessary to input the teaching signal. However, the connecting weight changes according to the changing of the teaching signal. This model can also easily accommodate changes in the environment. In each scene, optimal learning is possible. Moreover, the deep learning method is proposed recently [15]. It is a kind of algorithms in the learning model. It attempts to high-level categorizing data using multiple non-linear transformations and one method of machine learning. In the field of image recognition and speech recognition, the deep learning method has attracted the attention. We suggested the possibility of realization about the hardware implementation of the deep learning model. It will improve the artificial intelligence element with self-dynamical learning. The realization of an integration device will enable the learning time to be reduced. The proposed model is robust with respect to fault tolerance. Future tasks include system construction and mounting a large-scale integration.

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