EFFECTS OF BALANCED EXCITATION AND INHIBITION IN ARTIFICIAL VISION USING NEOCOGNITRON

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Abstract: The visual pathway of the human being is very complex to understand in terms of the information processing from the retina to brain and recognize the visual patterns trained by either supervised learning or unsupervised learning. There are mainly two types of nerve cell to recognize any characters or patternsare excitatory neuron cells or inhibitory neuron cells. These cells are responsible to recognize pattern very efficiently if only if excitation and inhibition are proper balanced. If imbalance in excitation and inhibition shows significant effect of this to not recognized the global and local features of a pattern properly.In this research paper we will discuss and elaborate the visual pathway and an artificial neural network proposed by Fukushima for artificial vision i.e. Neocognitron[1], is hierarchical structured , consist of various stages with Simple and Complex cells for pattern reorganization. Effects of balanced of excitation and inhibition to recognized the global and local features of visual patterns.

Keywords: Artificial Vision, Neocognitron, Excitation and inhibition balanced, convolution neural network.

I. INTRODUCTION

The visual pathway of the human being is very complex to understand in terms of the information processing from the retina to brain and recognize the visual patterns trained by either supervised learning or unsupervised learning. There are mainly two types of nerve cell to recognize any characters or patterns are excitatory neuron cells or inhibitory neuron cells. These cells are responsible to recognize pattern very efficiently if only if excitation and inhibition are proper balanced. If imbalance in excitation and inhibition shows significant effect of this to not recognized the global and local features of a pattern properly.. In the first section we will discuss about the basic concepts and architecture of Neocognitronis hierarchical structure , consist of various stages with Simple and Complex cells for pattern reorganization. In next section elaborate the Convolution Neural Networks (CNNs) like the neocognitron are inspired by the classical hypothesis of Hubel and Wiesel, and have some build-in shift and distortion invariance. CNNs have three architectural ideas: Local receptive fields shared weights and often sub sampling. Visual pattern recognition, such as reading characters or distinguishing shapes, can easily be done by human beings, but it is very difficult to design a machine which can do it as well as human beings do. In the next section we discuss about the effects of balanced of excitation and inhibition to recognized the global and local features of visual patterns. In the last section of this research paper we presents the results comes from the Neocognitron .Net based tool that shows the role of balanced excitation and inhibition.

II. NEOCOGNITRON

The neocognitron is a hierarchical neural network consisting of many layers ofcells. The initial stage of the network is the input layer consisting of a two-dimensional array of receptor cells. Each of the succeeding stages has a layer of ‘S-cells’ followed by a layer of ‘C-cells’. S-cells are feature-extracting cells. C-cells are put into the network to allow for positional error in the features extracted by the S-cells. Thus, in the entire network, layers of S-cells and C-cells are arranged alternately.

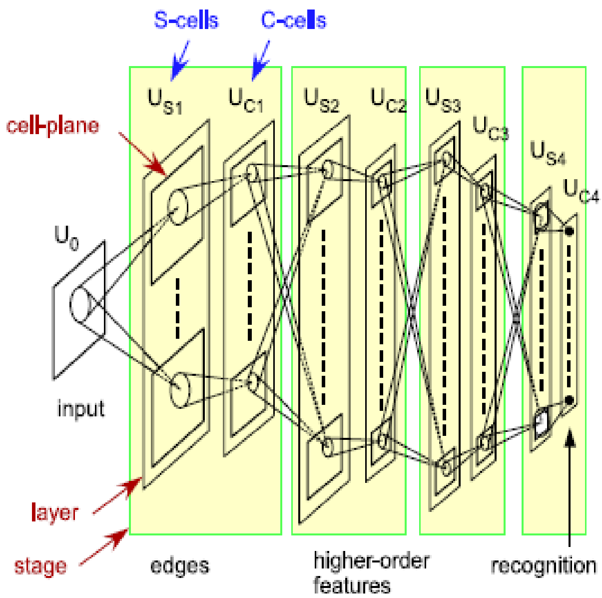

Fig.1 Schematic diagram illustrating the inter-connecrions between layers in the Necognitron.

The layer of C-cells at the highest stage is the recognition layer.[2] Working Of Layers is as follows:

• UG Layer (Contrast Extraction): Layer UG consists of on-center cells, and one off-centercells. The output from layer UG depends upon spatial orientation of the input connectionsand is equal to zero in the area of flat intensity.

• US1 Layer (Edge Extraction): Layer US1 is an edge-extracting layer. The S-cells istrained using supervised learning. Due to supervised learning for the feature's location.The cell with coinciding receptive field center with that of that specific feature, takes theplace of seed cell of that cell-plane, and it reinforces the output automatically.

• Intermediate Layers (Competitive Learning): The S-cells of stages second and third thatis, US2 and US3, are automatically self-organized by using unsupervised competitivelearning technique as in original work [3].Winner-take-all technique detects the seed cell.

• Highest Layer (Supervised Learning): The highest stage S-cells (US4), are trained by asupervised competitive learning technique. The learning rule we used here is same as thecompetitive learning that is being used for the training of US2 and US3. At this stage thegiven class labels of the digitized handwritten digit training patterns also used for the samepurpose. In the case of many deformed digitized handwritten digit training patterns morethan one cell-plane is generated to take care of the deformed handwritten digit pattern forone class, in US4. Therefore, the class name of digitized training pattern is allocated to thecell-plane during learning.[3] Each cell receives its input connections from only a limited number of cellssituated in a small area on the preceding layer. Each C-cell receives signals from a group of S-cells that extract the same feature, but from slightly different positions. It is activated if at least one of these S-cells is active. We can also say that thespatial response of a C-cell layer is a blurred version of the response of the S-cell layer preceding it.[4]

III. CONVOLUTION NEURAL NETWORKS

Convolution Neural Networks (CNNs) like the neocognitron are inspired by the classical hypothesis of Hubel and Wiesel, and have some build-in shift and distortion invariance. CNNs have three architectural ideas: Local receptive fields shared weights and often sub sampling. Visual pattern recognition, such as reading characters or distinguishing shapes, can easily be done by human beings, but it is very difficult to design a machine which can do it as well as human beings do. We believe that the best strategy is to learn from the brain itself. We are studying the mechanism of visual information-processing in the brain, and trying to use it as a design principle for new information processors. More specifically, we are studying how to synthesize a neural network model which has the same ability as the human brain. As a result of this approach, a pattern-recognition system called the "neocognitron" has been developed. Such neural networks in the brain are not always complete at birth. They gradually develop, adapting flexibly to circumstances after birth. Sophisticated brain functions, such as learning, memory, and pattern-recognition, are believed to be acquired through the growth of the neural network, in which neurons extend branches and make connections with many other neurons.[5]

IV. EFFECTS OF BALANCED EXITATION AND INHIBITION IN VISUAL CORTEX

In addition to measuring the total input conductance, we have also attempted to distinguish the components of the conductance changes arising from excitatory and inhibitory synaptic inputs. This distinction is based on the assumption that the changes in input conductance are entirely synaptic. Using this approach, we studied the orientation tuning of synaptic excitation and inhibition and found that they were similar. This similarity would be predicted if intra-cortical excitation and inhibition originated from cells with similar orientation tuning and would explain previous reports that orientation tuning is not sharpened by intra-cortical inhibition. The Neocognitron is the best choice to demonstrate the balancing between excitation and inhibition for visual perception and pattern recognized.[6]

V. SIMULATION TOOL

The Simulation softwarewe used here for demonstration of the Neocognitron and its balanced excitation and inhibition of different types of pattern(deformed ,shifts in position etc.) is .NET based Neocognitron V.0.1.We used this simulator tool for illustrated with different type of patterns before learning and after learning and orientation selectivity for different stages.

VI. RESULTS AND DISCUSSION

Finally, we discussed in this section the results of simulators software that we used. In the Fig. 2 we described the structure of the 29x29 size of plane Neocognitron. In the Fig. 3 shows the train of the neocognitron. In the Fig. 4 the output value of 0.3083.Exitation and inhibition is balanced. Fig. 5 shows the Input of a defective pattern and train the network and in Fig 6 the output value is 0.1410. Fig.7 shows the input a new pattern that is supervised learned with the network and Fig. 8 shows the recognized pattern with 0.0951 output value. Fig. 9 shows the input the deformed pattern and train the network and finally, in Fig 10 we get the 0.0681 output value. So we can say that the effects of balanced excitation and inhibition varies from the pattern extracted featured and output values of different orientation selectivity of multiple stages input values.

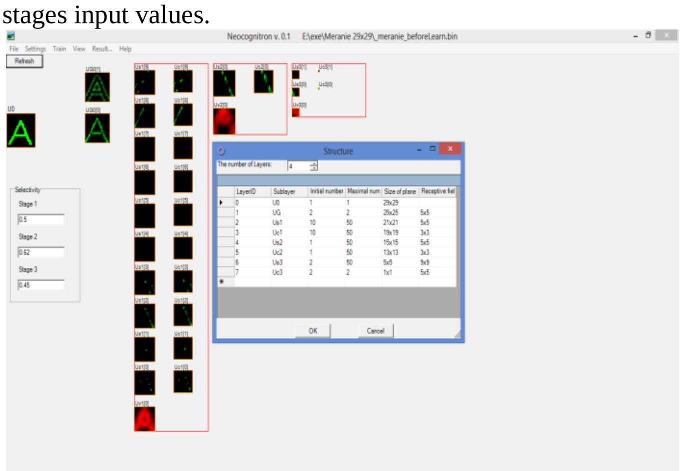

Fig. 2 Structure of the Neocognitron Size of plane is 29x29 pixels with 4 layers.

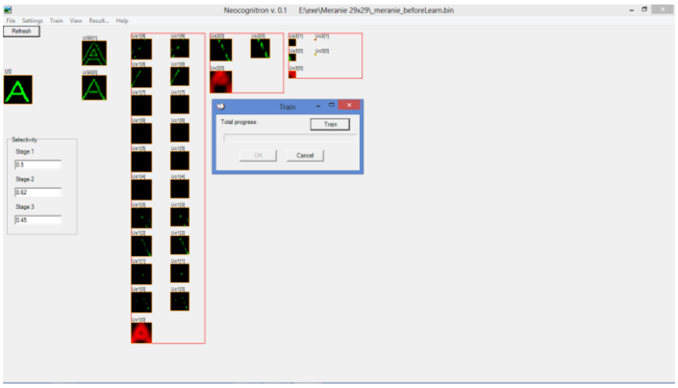

Fig .3 Train the Network

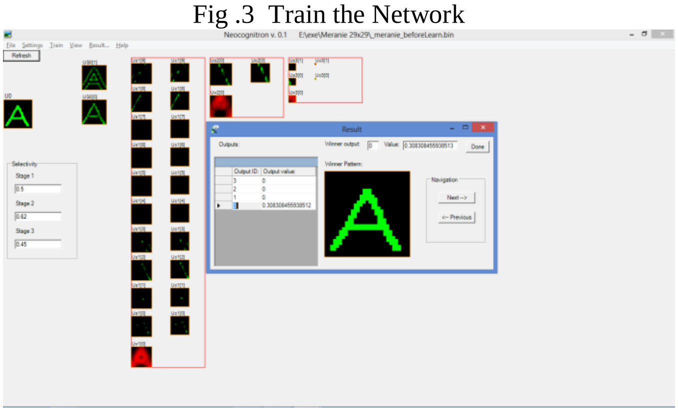

Fig. 4 Recognization of character / pattern output value 0.3083.Exitation and inhibition is balanced.

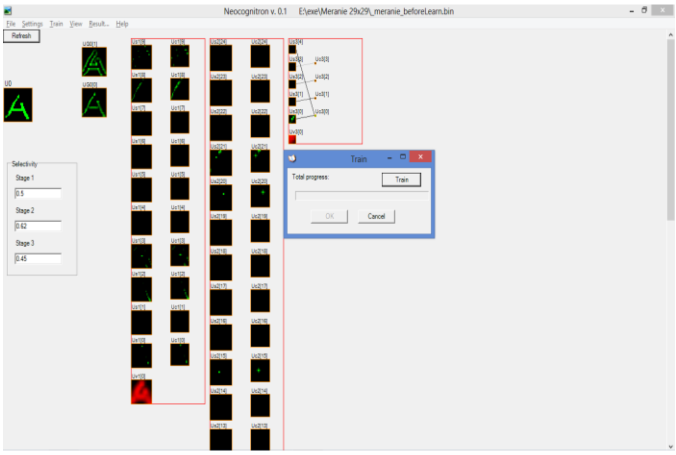

Fig.5 Train Neocognitron with Defective Text.

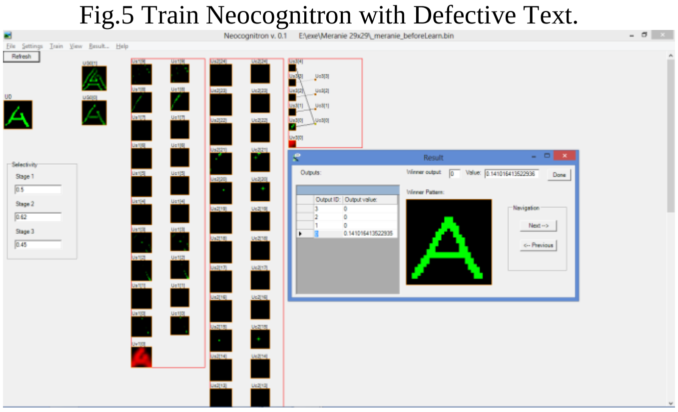

Fig.6 Recognization of character/pattern output value 0.1410.

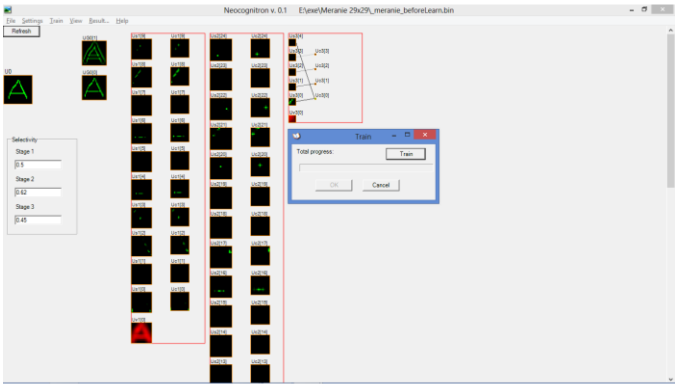

Fig..7. Input a new pattern “A” to train the Network.

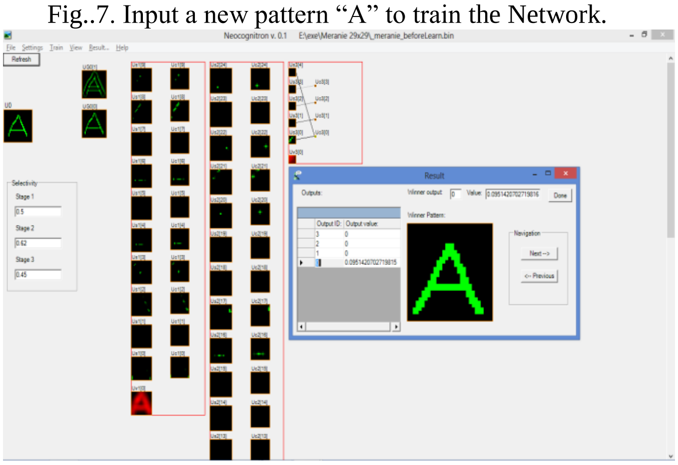

Fig. 8 Recognize the pattern “A” with 0.0951 output value.

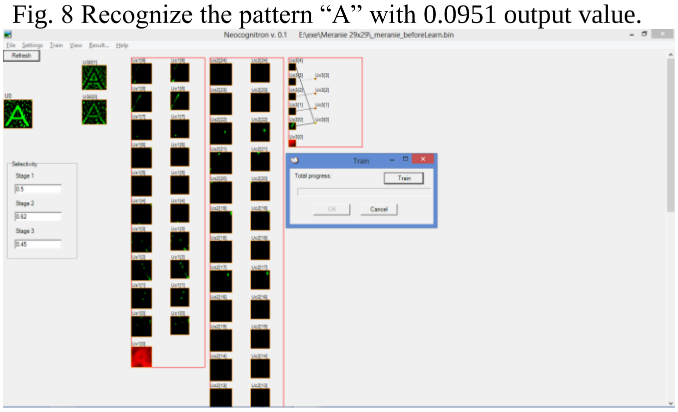

Fig. 9 Train Neocognitron with the deformed pattern.

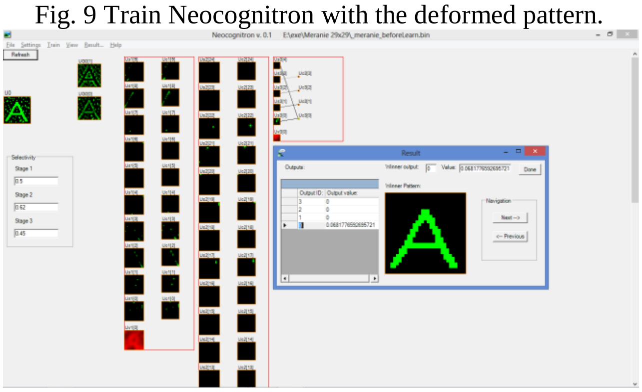

Fig. 10 Recognize the deformed pattern with 0.0681 output value.

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