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Performance Analysis on Learning Algorithms with various Facial Expressions in Spiking Neural Networks

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***Abstract*— This paper is based on different expression classification and facial action recognition performed using human face database. This work aims to classify different facial expressions of the individuals from the static facial images from the JAFFE database with an improved spike model which is trained with the certain learning algorithms to recognize, the kind of expression with different poses such as happy, sad, neutral, fear and neutral.. This work challenges towards the development of more accurate and automated facial expression recognition methods of expressions.**

I. INTRODUCTION

Facial expression analysis/recognition1has interested, due to its various purposes and applications. It plays an important role in emotion recognition and thus contributes to the development of human computer interaction systems.[1] It can also implement face recognition systems by providing prior knowledge on the facial motions and facial feature deformations. This is particularly considering that the mouth area contains significant amount of discriminative information, yet it is where most of the facial deformations take place. Other applications include, but are not limited to psychological studies, tiredness detection, facial animation, robotics as well as virtual reality. [3]Facial expressions are generated by facial muscle contractions which result in temporary facial deformations in both facial geometry and texture.

II. BACKGROUND

A. Basic Emotions vs. Action Units

The two main streams of facial expression analysis have been message-based approaches and sign-based approaches. [2]The message-based approaches focus on interpretation of specific facial patterns and classify expressions into a predefined number of discrete categories, in which the most commonly used are the six basic emotions as anger, disgust, fear, happy, sad and surprise.The sign-based approaches, on the other hand, provide descriptions for facial deformations at an abstract level in an objective manner and defer the decision making process to other high-level algorithms or human experts. Hence, most of the studies on facial expression analysis rely on the categorization of expressions.

III. NETWORK ARCHITECTURE

A. Spiking neural networks

In Spiking Neuron Networks, the timing of each spike is considered as the means of communication and neural computation. [9]This spiking neurons compares with traditional neuron models where analog values are considered, representing the rate at which spikes are fired. The neurons transmit information to each other by means of trains of action potentials, which are called spikes. These spikes can be recognised by placing microelectrodes in the extracellular or intracellular medium and recording the electric potential difference between the signal and reference electrode

B. Feed Forward Neural Networks

The network follows a feed forward path, where as the feed forward neural network is an artificial neural network, in which the connections between the nodes, do not form a directed cycle. [10]In this network, the information moves in one direction only, from the input nodes, through the hidden nodes and to the output nodes. and also there are no cycles or loops in the network.

IV. LEARNING RULES OF NN

There are many types of Neural Network Learning rules, and they fall into two broad categories:

- Supervised learning,
- Unsupervised learning.

The learning rule provides a training set of proper network behaviour:

$$\{x_1, d_1\} , \{x_2, d_2\} , \ldots \{x_n, d_n\} \qquad \text{eq (1)}$$

where (x_n) is an input to the network, (d_n) is the correct target output. When the inputs are applied to the network, its output is compared with the targets. Hence the learning rule is then used to adjust the weights and the biases of the network is adjusted to move, such that the network outputs is closer to the targets.

A. Supervised Learning

In supervised learning, [5] consider that at each instant of time when the input is applied, the desired response of the system is provided by the teacher.

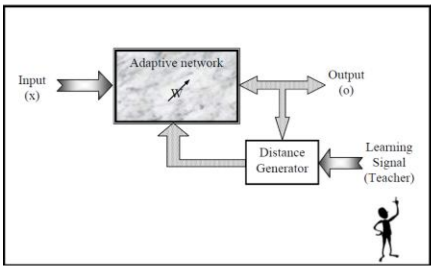

Fig 1. Block diagram for explaining of supervised learning.

B. Unsupervised Learning

In unsupervised learning, the weights and biases are modified in response to network input only. There are no target outputs available.[4] How can you train a network if you don't know what is supposed to do?.Many algorithms perform some kind of clustering operation. Those algorithms learn to categorize the input patterns into a finite number of classes. This is useful in such applications such as vector quantization.

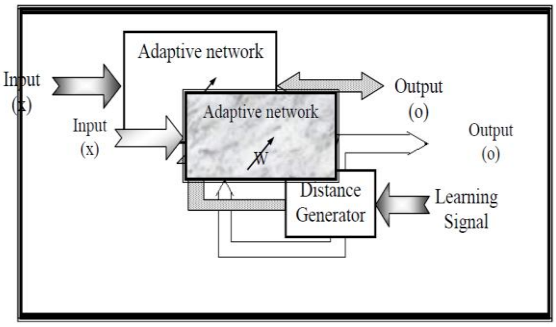

Fig 2.Block diagram for explaining of unsupervised learning.

Unsupervised learning is sometimes called learning without teacher.

V. LEARNING ALGORITHMS USED

A. Reinforcement Learning Rule

The reinforcement learning rule requires of:

1. A set of nodes as states *S*;
2. A set of performed actions *A*;
3. Rules of transitions between states;
4. Rules that determine the scalar immediate of a transition.

5.Rules which explain that what the agent observes.

These techniques initialize with the value of an objective transfer function for the initial states. The value is backed up to all states from which each final state which can be reached in one step. By using, the known transition probabilities, the existing states, are the assigned values.[6] The process continues until the final state assigns its value.

When the value function is learned, the optimal action is selected for the other states by assigning the action that maximizes the expected value of the next state. Now the learned value function is assumed to be a prediction of the sum of future values. The values defined by the problem's objective function are called reinforcement learning.

B. Delta Learning Rule

The Delta learning rule is valid for continues activation functions, and it is a type of supervised learning. The weights are initialized at any values for this method of training. [7]It is also called the continuous perceptron training rule.It is also called as continuous perceptron training rule. The delta learning rule can be generalized for multilayer networks.

C. Competitive Learning Rule

Competitive Learning is implemented with Neural Networks which contain a hidden layer and is commonly known as "competitive layer".Every competitive neuron is described by the weights, which learning is a form of learning, whereas, in artificial neural networks, the nodes compete for the right to respond to a subset of the input data. The weights which is assumed in this learning method is termed be as

$$\mathbf{w}_i = (w_{i1}, .., w_{id})^T, i = 1, .., M \qquad \text{eq(2)}$$

calculates the similarity measures in between the input data.

D. Hebbian Learning Rule

The Hebbian learning rule is that, whenever there are two cells having similar activations, the weights which connect them should be increased so that the connected neurons connects each other to the support learning.[8] Hebb introduced the concept of increasing weights, but not decreasing weights. In pattern recognition , this provides the means to strengthen weights when inputs are similar, and to weaken them when they are dissimilar. The Hebbian rule is defined in the following equation

$$\Delta W_{ij} = \sum x_i y_j \qquad \text{eq(3)}$$

where $\sum$ is a learning rate where x is the input, y is the output, and W_{ij} is the weight that connects the input and output. The Neural Network uses the Hebbian rule is a very simple network that utilizes some number of input cells, and same set of output cells .The network is fully interconnected with weights connecting between each output cell and each input cell so that every input has some influence over the output. To train the network and build the association between input and output cells, and so the network must be provided with the input pattern and retain the false value of the input at the output. The weights have been trained by the Hebbian learning, the network can recall output patterns from those presented to the input. The major disadvantage in Hebbian rule is that, it can

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create map over orthogonal patterns of inputs. This can be due to the lack of hidden layer within the network.

VI. RESULTS AND DISCUSSION

The MATLAB software is used in the simulation process with the two following databases as explained below:

A. Dataset

To develop and evaluate the facial expressions, large collections of training and test data are needed. Figure 3. Few Sample of facial images in JAFFE Database

Fig 3. Few Sample of facial images in JAFFE Database

This paper requires the [7] JAFFE and FACS Database. The database contain 213 images of 7 facial expression (6 basic facial expressions+1 neutral) posed by 10 Japanese female models in JAFFE Database and. Each image has been rated on 6 emotions adjectives by 60 Japanese subjects

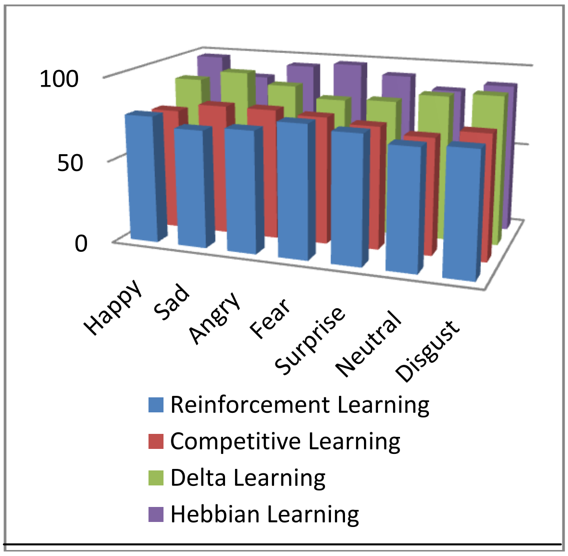

Fig 4. Expression wise Recognition Rate comparison Different Learning Algorithm with JAFFE Database

The MPI facial expression Database which contain various emotional and conversational expressions. The database contains of the images of 55 different facial expressions having the method-acting protocol, which guarantees the well-defined and natural facial expressions and converted to pulses.

Fig 5. Few Sample of facial images in MPI Database

The match between the input pattern and classifier should make the output neuron easier to fire a spike, and thus should result in a higher firing rate. The input spike trains are generated based on the binary image by thresholding and filtering the input image.

Using the two datasets the image is transformed into binary spikes and learned by the listed algorithms above and compared totally with all their required result to test its accuracy and fast learning rate with less amount of time.

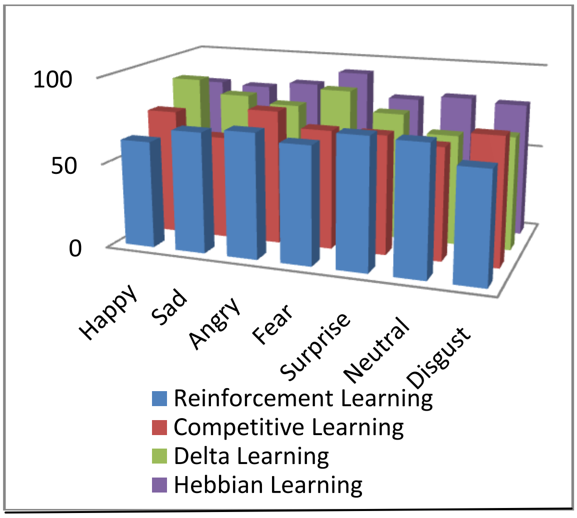

Fig 6. Expression wise Recognition Rate comparison Different Learning Algorithm with MPI Database

The results are averaged and compared with recognition rate, spike rate and training time and compared to obtained the highest rate for expression recognition.

Learning Algorithm Used	*Training Time (ms)*	*Spike Rate (ms)*	*Recognition Rate*
Reinforcement Learning	96.87	145.7596	79.43%
Competitive Learning	115.02	206.1565	82.71%
Delta Learning	146.77	215.7701	92.86%
Hebbian Learning	165.84	278.121	95.02%

Table 1. Results compared with different Learning

Also the compared recognition rate of the two databases are listed below

Database	*Overall Recognition rate*
JAFFE Database	90.21%
MPI Database	83.09%

Table 2. Results compared with the databases during recognition

VII. CONCLUSION

This work is to recognize the facial expressions of the images contained in the JAFFE and MPI database using spiking neural networks with different learning algorithms to improve the classification. The presented system is able to correctly classify the expressions in different expression groups (neutral, angry, disgust, fear, sad, happy and surprised). This work is also suitable in recognizing a person's identity specification in security purpose and also in medical imaging etc.The presented system of classification The current work could successfully classify a large dataset of static images in the database with seven different expression groups, efficiently used to recognize the expressions with an excellent recognition rate .

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