

*A Computational Model for the Biological
Underpinnings of
Infant Vision and Face Recognition*

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INTRODUCTION

- A scientists' challenge is to understand how an infant's brain learns to efficiently process visual information. An infant's range of focus is short for several months, and faces enter into this range more often than any other scene. Within a few months of birth, the brain can differentiate faces from other objects and an infant can recognize a known face from a stranger's. The repetition of face stimulus in conjunction with the relatively short time it takes for recognition to occur suggests there may be more regularity among facial stimuli, or perhaps a more sensitive information processing mechanism biased towards facial stimuli.

PURPOSE

- ✱ The main purpose of this project is to investigate the learning process of an infant's brain, using simulation by an artificial neural network (ANN) as a model.
- ✱ The biological hypotheses are based on plasticity (Hebbian learning) and well-established behavioral research on the role of response to low frequency in early stages (M. Banks et. al. 1981).
- ✱ After training the network on a set of “typical faces” and also on a few non-facial stimuli, the ANN will be tested with a previously unseen face as well as new objects.
- ✱ Higher success rates in tests for recognizing faces compared to other objects by the ANN suggests regularity amongst low frequency components of faces is essential for the brain to learn more efficiently to recognize a face.

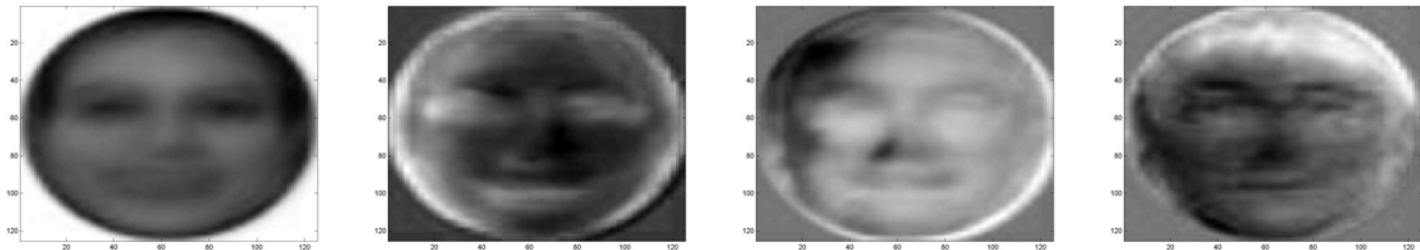
METHODS

Pictures of Eigenfaces

✶ Total data set consisted of black and white images, 125x125 pixels, frontal



A Few Eigenfaces



METHODS

Filtering Algorithm

- ✱ Principal Component Analysis (PCA): solving the covariance matrix of vectorized faces for eigenvalues and eigenvectors.
- ✱ Calculate how many eigenvalues carry 90% information with the equation
$$\frac{\sum \lambda}{\text{tr}(\lambda)}$$
- ✱ Project all faces along directions of the eigenvectors corresponding the eigenvalues found in the previous step.

NEURAL NETWORK ARCHITECTURES

- ✨ Infants experience the world through all senses, some more developed than others.
- ✨ The visual learning of mother's face or (other caretakers) is accomplished by feedback from a combination of touch, taste, smell, sound.
- ✨ During earlier developmental stages, there are communication pathways between the visual and other sensory areas of the cortex.
- ✨ The biological network is self-organizing. For theoretical study, a model with feedback (as if from other senses) provides comparable “behavioral” output.

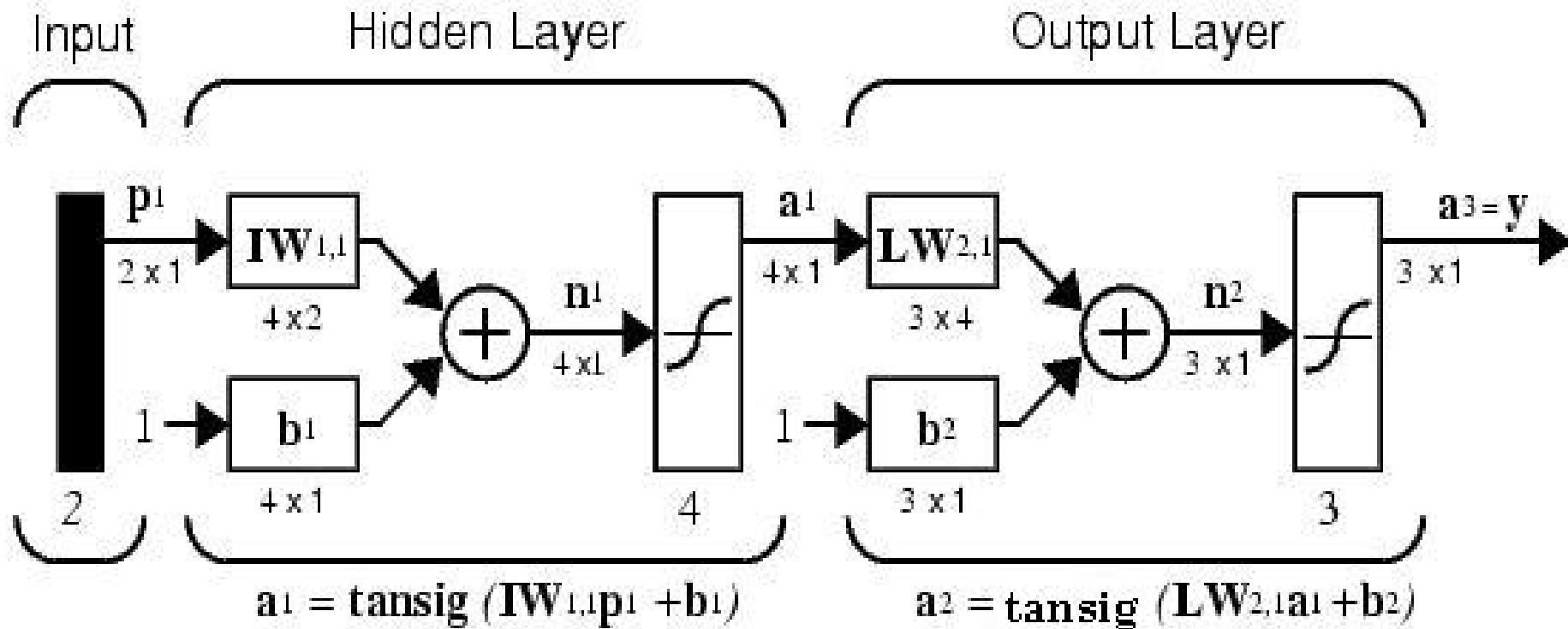
NEURAL NETWORKS

Feedforward Backpropagation Model

- ✱ The input units are eigenfaces representing at least 90% of the information found in the entire set of 68 faces.
- ✱ In the hidden layer and output layer, there are as many neurons as eigenfaces.
- ✱ Feedforward: Multiplying each input by a weight matrix and taking the hyperbolic tangent function of entries of this matrix.
- ✱ Backpropagation: Finding the error between the expected output and actual output, altering the weight matrices, and “feedforward” again until the error is no more than 10%.

NEURAL NETWORKS

Feedforward Backpropagation Model

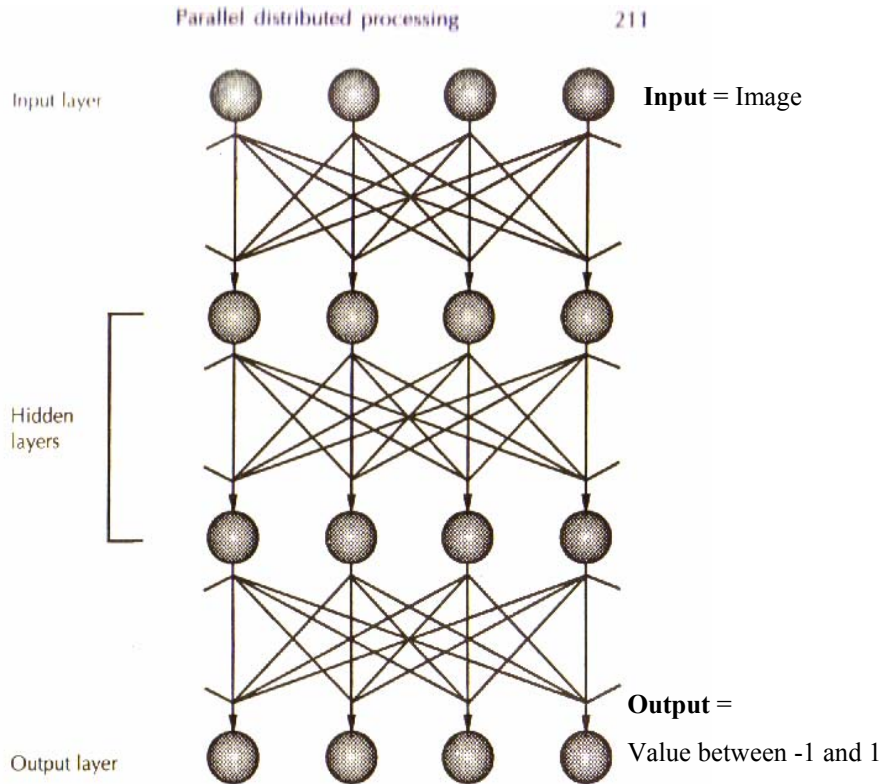


RESULTS

- ✱ The network was trained on 15 eigenfaces, which represented 95% of the entire data set. After 6 epochs, total error was 8%.
- ✱ The network was then trained on a previously unseen face, and average performance was better than 90%.

METHODS

Neural Network Output



☀ Present image to NN.

☀ Output is correlation between input image and “average face”.

☀ Value close to 1 indicates face, less than 1 non-face, and 0 undetermined.

Figure 10.2 Connections between the layers of artificial neurons in a PDP network.

RECOGNITION OF FACE VERSUS NON-FACE

- In accordance to behavioral research, early infant vision responds to **low frequencies only.**
- Low – Pass Filter is used to remove high frequency components.
- Generalized Hebbian Learning is applied for principal components extraction.
- Multilayer Perceptron based on Back Propagation Algorithm is used for classification: Face or non-Face

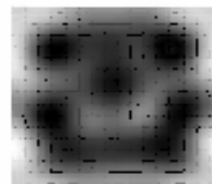
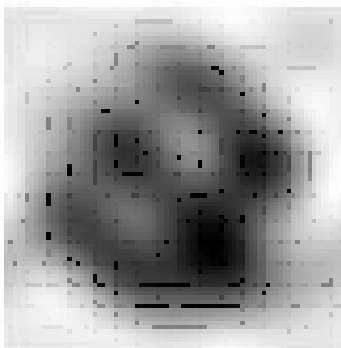
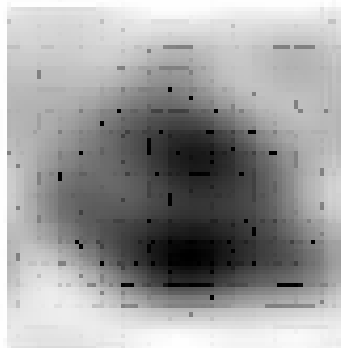
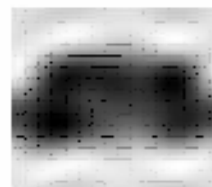
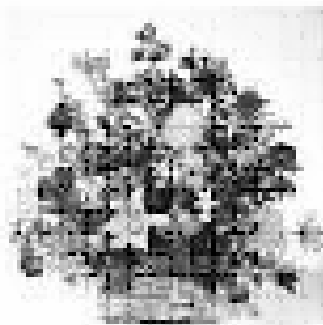
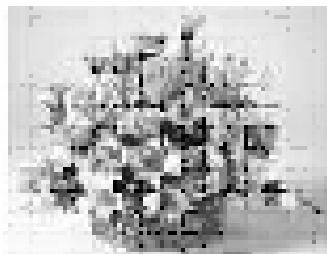
Filters



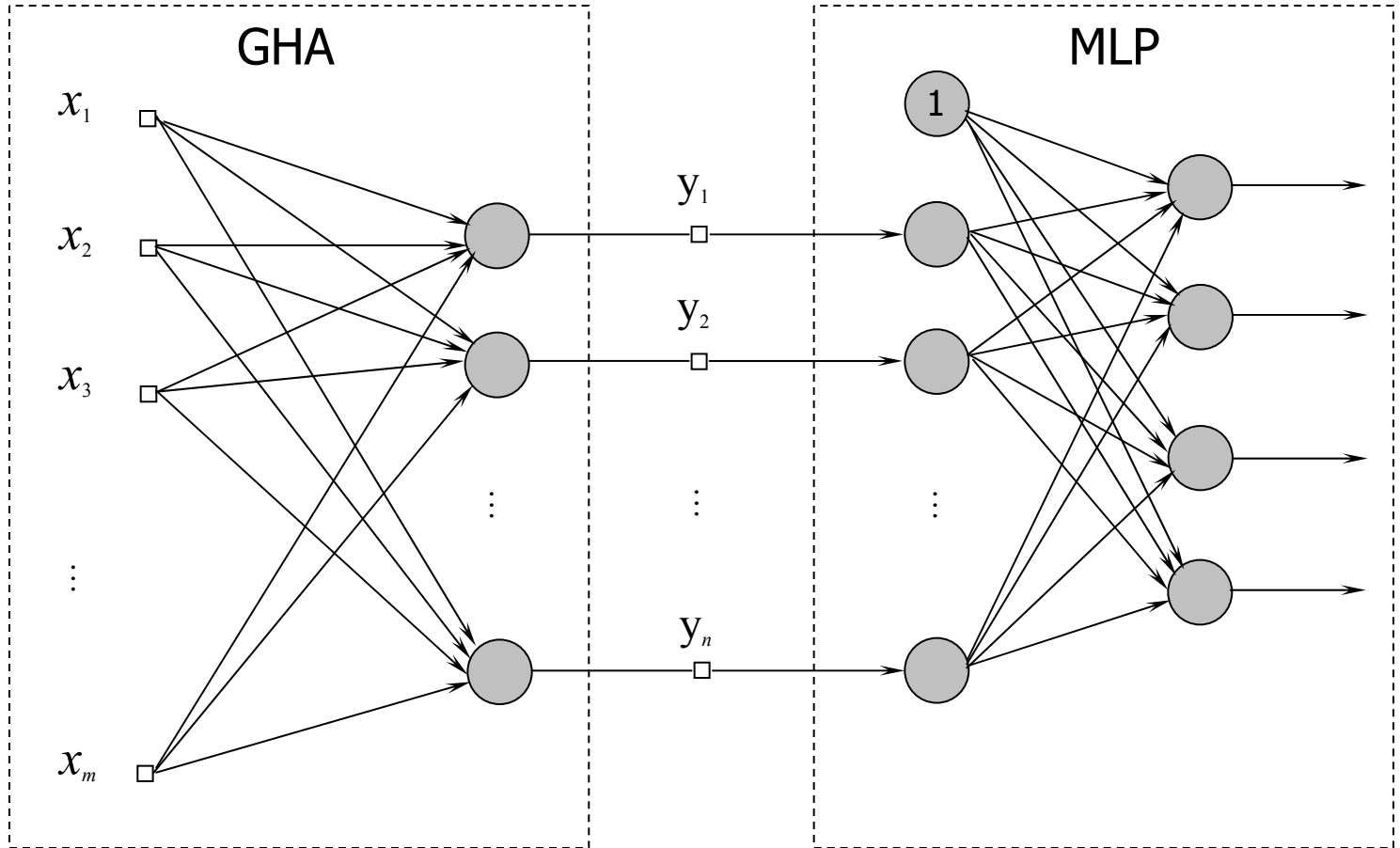
Image after
passing filters



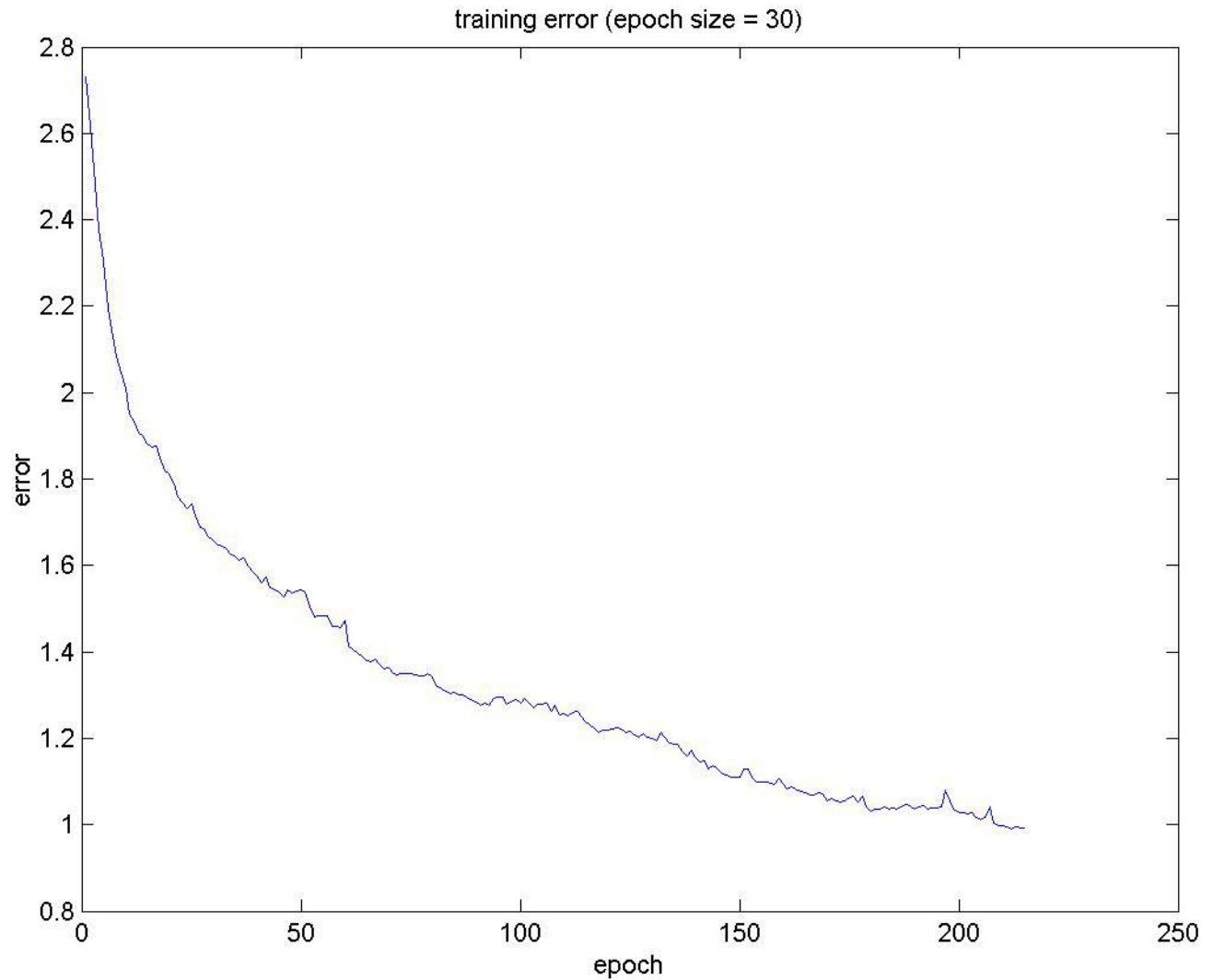
Examples of Filtered Non-face Images



Neural Network Design



Training error



Training and Testing Results

- All the training and testing samples are images after passing the same low-pass filter (5%).
- 100% accuracy for 30 training samples, 16 for faces, 14 for non-faces
- 100% accuracy for testing samples, 4 for faces, 4 for non-faces.

REFERENCES AND ACKNOWLEDGEMENTS

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