ABSTRACT

Two subsystems that could be utilized in the creation of a face recognition system were investigated, a face detection subsystem, and a normalization subsystem. The detection of a face in a digital image is not a simple process and numerous methods have been proposed to accomplish this. Among these methods the face detection via color segmentation method is investigated. This method involves detecting pixels of ‘skin’ color in the image, then grouping and filtering to determine which sets are likely to contain a face. This method was found to be very susceptible to variations in lighting and background colors. Grouping and filtering to determine like face candidates was also very error prone. Overall, face detection via color segmentation was found to be insufficient to accurately detect faces in images.

The normalization process is the process of removing variations in the facial image and preparing the image for the recognition process. A method based on neural networks performing a nonlinear PCA (Principle Component Analysis) of the face images was investigated. No neural network was found that was able to perform this transformation successfully. Although on some training image sets, some network configurations were trained to produce rudimentary results similar to those expected from the desired nonlinear PCA transformation. Recommendations are made as to how to continue research in this area.

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1. INTRODUCTION AND BACKGROUND

The ability to automatically locate and identify individuals in a digital photograph has numerous applications. There are commercial systems that are beginning to be used in various security areas. One of the most controversial examples is the installation of face recognition software for surveillance in public places like airports [ACLU 2001]. Although face recognition systems for crowd surveillance have not performed well [ACLU 2003], commercial face recognition systems are being used in other security areas. For example, The Department of Motor Vehicles in the state of Illinois is one of a number of states that has integrated it into its state drivers' license program to help deter identity theft [Viisage 2004]. An important difference in these two applications is related to the control of the image setting. In the drivers' license office subjects can be positioned, asked to remove headwear, and lighted in a consistence manner. This control of pose and lighting is not viable in the crowd surveillance application.

The use of face recognition to categorize digital photographs for a digital photo album has had some commercial success. Fuji film has recently demonstrated a prototype device in which the user has the ability to sort their images by face. Enabling the user to select a family member or friend from a menu and then view a folder of all that person's images, regardless of setting or other external factors [Digitalcamerainfo 2005]. This technology would allow a user to quickly sort and categorize their digital photos.

Although some commercial products are being produced, there is still a lot of research being preformed to find better methods for face recognition. The general face recognition problem can be broken down into three major steps. First the face detection system must locate faces in images. Secondly, a normalization routine is often used to compensate for variations in pose, lighting, scale factor, and expression. Finally an identification algorithm is employed to make the identification. At this time, major research efforts are underway in all three areas [Zhao 2003].

1.1 Face Detection Algorithms

Face detection attempts to locate all the faces in an image. As one might suspect, this can be a very difficult process for an arbitrary image. Among the many factors that complicate this process are pose, presence or absence of structural components, facial expressions, occlusion, orientation, and imaging conditions [Yang 2004]. (See Appendix A for an explanation of these terms).

Numerous methods have been examined as possible solutions to the face detection problem. The choice of method depends directly on the original image source. Video tracking applications have access to time sequential images. This additional information makes detecting faces in video series an easier problem than detection in a still image [Yang 2004]. Color images also carry additional information that can be used in the detection algorithm. Face detection from a still grayscale image is the most challenging [Frischholz 2005] because the detection algorithm has the least information to work with. The bulk of the research in face detection has centered on detecting faces in still grayscale images. Although there has been some significant work in both video and color face detection.

Face detection algorithms for images can be categorized into four major categories: knowledge-based methods, feature invariant approaches, template matching methods, and appearance-based methods [Yang 2002]. A substantial portion of recent research has focused on appearance-based methods. Some of the algorithms frequently sited in the literature are summarized in this section.

1.1.1 Skin Color Filtering

Skin color filtering is possible because distributions of skin-colors of different people of multiple races are clustered in chromatic color space. Although skin colors of different people appear to vary over a wide range, they differ much less in color than in brightness. In other words, skin-colors of different people are very close, but they differ mainly in intensities [Yang 1996].

The segmentation of skin color is mostly used as a first approximation for the localization of faces. This allows a reduction of the search area for other more precise and computationally expensive facial feature detection methods. One of the main advantages of using skin color is that it is orientation invariant. A second advantage is the speed of processing. This is one of the faster facial feature detection methods available [Storring 1999].

Skin detections methods range in complexity from simple bounding rules in a given color space to Bayes skin probability map classifiers and Gaussian methods based on an elliptical Gaussian joint probability density function. In addition to a multitude of algorithms many of these algorithms can be applied in multiple color spaces [Vezhnevets 2003].

1.1.2 Principle Component Analysis / Eigenfaces

The eigenfaces technique uses principal component analysis (PCA) in an attempt to determine which features of the face are important for classification. This analysis also reduces the dimensionality of the training set [Lawson 2005]. This is accomplished by projecting “face images onto a feature space that spans the significant variations among a set of known face images. The significant features are known as "eigenfaces," because they are the eigenvectors (principal components) of the set of faces. The projection operation characterizes an individual face by a weighted sum of the eigenface features. Each individual face can be represented exactly in terms of a linear combination of the eigenfaces…Each face can also be approximated using only the "best" eigenfaces--those that have the largest eigenvalues, and which therefore account for the most variance within the set of face images. The best m eigenfaces span an m-dimensional subspace - "face space" - of all possible images [Turk 1991].”

Using the notation and equations of Belhumeur, Hespanha, and Kriegman [Belhumeur 1997], consider a set of N sample images $\{\mathbf{x}_1, \mathbf{x}_2, ..., \mathbf{x}_N\}$ taking values in an n-dimensional image space, where the pixel values of each image are written as the column vectors $\mathbf{x}_i$. A linear transformation mapping the original n-dimensional image space into an m-dimensional feature space, where m < n, can be defined by the transformation

$$\mathbf{y}_k = W^T \mathbf{x}_k \qquad k = 1, 2, ..., N \tag{1.1}$$

where $\mathbf{y}_k \in \mathbf{R}^m$ are feature vectors and $W \in \mathbf{R}^{nxm}$ is a matrix with orthonormal columns. If the total scatter matrix S_T is defined as

$$S_T = \sum_{k=1}^{N} (\mathbf{x}_k - \boldsymbol{\mu})(\mathbf{x}_k - \boldsymbol{\mu})^T \tag{1.2}$$

where $\boldsymbol{\mu} \in \mathbf{R}^n$ is the mean image of all samples, then it can be shown that the scatter of the transformed feature vectors $\{\mathbf{y}_1, \mathbf{y}_2, ..., \mathbf{y}_N\}$ is $W^T S_T W$ [Belhumeur 1997]. "In PCA, the projection W_{opt} is chosen to maximize the determinant of the total scatter matrix of the projected samples, i.e.

$$W_{opt} = \arg\max_W \left| W^T S_T W \right| = \left[\mathbf{w}_1 \; \mathbf{w}_2 \; \ldots \; \mathbf{w}_m \right] \tag{1.3}$$

where $\{\mathbf{w}_i \mid i = 1, 2, ..., m\}$ is the set of n-dimensional eigenvectors of S_T corresponding to the m largest eigenvalues. Since these eigenvectors have the same dimension as the original image they are often referred to as Eigenpictures and Eigenfaces [Belhumeur 1997]."

The most important feature of PCA when applied to face images is its ability to capture the features that are important to face recognition and detection in a dimensional space that is much smaller than the original dimensions of the image. Thus, for face detection a candidate image can be projected onto "face space". The distance in "face space" between the candidate image and the cluster of known facial images can be used as an indication of the existence of a face in the candidate image [Jung 2002]. Given this, an obvious approach to the face identification process is to simply use a nearest neighbor classification scheme in the face space to classify an unknown image.

Unfortunately, the PCA approach has a major disadvantage for the face identification process. Different lighting and poses among images of the same individual generally account for a much larger variation in the image than image variation due to different individuals [Moses 1994]. The PCA method maximizes the total scatter across all images of all faces. By maximizing the total scatter, variations due to lighting and pose are retained and may be the most significant features of the face space. Thus, while PCA projections are optimal from a dimensional reductions basis, they are not optimal from a discrimination standpoint [Belhumeur 1997]. The result is that the face space created using the PCA method is useful for face detection. However, it leads to difficulty if used for the identification process in images with variations in lighting and pose.

Another interesting feature of the PCA approach is that it can be implemented using a neural network [Turk 1991]. During the training process a neural network is trained to compress and reconstruct input images through a small number of hidden units. The output of the hidden units is a compressed representation of the image. It has been proven that when such a network reaches the global minimum of the reconstruction error, the values formed on the output of the hidden nodes are exactly the same as the first principle components, if a linear activation is used. If non-linear activation functions are used the output from the hidden units resemble principal components and represent the input image better than a linear network [Bryliuk 2001].

1.1.3 Fisher Linear Discriminant / Fisherfaces

The Fisher Linear Discriminate (FLD) method is a class specific linear projection method. FLD seeks to overcome the limitations of PCA by using a linear projection to a reduced dimensional space that maximizes the ratio of the between-class scatter and the within-class scatter. If multiple images of the same person are considered the same class, this method creates a face space in which individuals can be more readily identified [Belhumeur 1997].

Continuing with the notation of Belhumeur, Hespanha, and Kriegman, assume that each image belongs to one of c classes $\{X_1, X_2, ..., X_c\}$ [Belhumeur 1997]. The FLD "method selects W in [equation 1.1] in such a way that the ratio of the between-class scatter and the within-class scatter is maximized. Let the between-class scatter matrix be defined as

$$S_B = \sum_{i=1}^{c} N_i (\boldsymbol{\mu}_i - \boldsymbol{\mu})(\boldsymbol{\mu}_i - \boldsymbol{\mu})^T \tag{1.4}$$

and the within-class scatter matrix be defined as

$$S_W = \sum_{i=1}^{c} \sum_{\mathbf{x}_k \in X_i} (\mathbf{x}_k - \boldsymbol{\mu}_i)(\mathbf{x}_k - \boldsymbol{\mu}_i)^T \tag{1.5}$$

where $\boldsymbol{\mu}_i$ is the mean image of class X_i, and N_i is the number of samples in class X_i. If S_W is nonsingular, the optimal projection W_{opt} is chosen as the matrix with orthonormal columns which maximizes the ratio of the determinant of the between-class scatter matrix of the projected samples to the determinant of the within-class scatter matrix of the projected samples, i.e.

$$W_{opt} = \arg\max_{W} \frac{\left|W^T S_B W\right|}{\left|W^T S_W W\right|} = \left[\mathbf{w}_1 \ \mathbf{w}_2 \ ... \ \mathbf{w}_m\right] \tag{1.6}$$

where $\{\mathbf{w}_i \mid i = 1, 2, ..., m\}$ is the set of generalized eigenvectors of S_B and S_W corresponding to the m largest generalized eigenvalues $\{\lambda_i \mid i = 1, 2, ..., m\}$, i.e.

$$S_B \mathbf{w}_i = \lambda_i S_W \mathbf{w}_i \qquad i = 1, 2, ..., m \tag{1.7}$$

Note that there are at most c-1 nonzero generalized eigenvalues, and so an upper bound on m is c-1 where c is the number of classes [Belhumeur 1997]."

Unfortunately, in the face recognition problem, S_W is generally singular because the rank of S_W is at most N – c, and generally the number of images in a learning set N is much smaller than the number of pixels in each image n. Belhumeur, Hespanha, and Kriegman proposed the following criterion for W_{opt}:

$$W_{opt}^T = W_{FLD}^T W_{PCA}^T \tag{1.8}$$

where

$$\begin{aligned} W_{PCA} &= \arg\max_W \left|W^T S_T W\right| \\ W_{FLD} &= \arg\max_W \frac{\left|W^T W_{PCA}^T S_B W_{PCA} W\right|}{\left|W^T W_{PCA}^T S_W W_{PCA} W\right|} \end{aligned} \tag{1.9}$$

which overcomes this singularity issue. This is equivalent to using PCA to reduce the dimension of the feature space to N – c and then, applying the standard FLD defined by equation 1.6 to reduce the dimension to c - 1. They referred to this technique as Fisherfaces.

The FLD method can be used in the same manner as the PCA method. An unknown image can be projected into face space and the distance between the image and each class be used to determine if the unknown image contains a face and to which class the face belongs if it does.

1.1.4 Other Methods

Many other face detection methods have been studied. Among the techniques frequently reported in the literature are naïve Bayes classifiers, support vector machines, mixture of factor analyzers, and the hidden Markov model [Yang 2002].

1.2 Normalization

The normalization process is intended to facilitate the identification process. The type of normalization performed depends on the methods of face detection and identification used. For example, if PCA is used for the detection and identification, the images are often normalized prior to projection into face space to reduce pose and illumination effects.

The general form of the normalization process can be described as a mathematical transform. Given I_{fc} , an image of face f under some arbitrary unknown condition c, the desire of the normalization process would be to find I_{f0}, the image of face f under some known standard condition 0. Mathematically, this can be represented by:

$$I_{f0} = T(I_{fc}) \tag{1.10}$$

This representation was proposed by [Shan 2003] as a representation for the normalization of variations in illumination. However, it can be extended as a representation for the normalization process for variations in any of the conditions described in Appendix A. If a suitable transformation T( ) can be found such that equation 1.10 is true for all conditions in a given set, that set of conditions can ideally be eliminated as a source of error in the identification process. For example, if a transform T( ) can be found such that, given a facial image lighted from any direction the same face under ambient lighting can be constructed, then errors from variations in lighting direction can be eliminated. Of course, in practice, finding such a transform for all possible lighting conditions is impractical. However, by placing reasonable limits on the domain over which T( ) is valid many facial image features can be compensated for. Some of the normalization methods for different conditions are presented below.

1.2.1 Variations in Illumination

Histogram Normalization

The objective of histogram normalization is to enhance the image detail without changing the structure. This is accomplished by altering the image so that its intensity histogram has a desired shape [Fisher 1994]. This process is called histogram equalization when the desired shape of the intensity histogram is a uniform distribution. However, it has been suggested by Jebara that by using the histogram of a well illuminated average human face as the desired shape of the intensity histogram an aesthetically appealing illumination can be created. To adjust for unequal lighting on different sides of the face, Jebara uses a gradated windowing histogram analysis. He further extends this method by eliminating areas of the face that are likely to have facial hair from the histogram generation process [Jebara 1996].

Other Methods

Numerous other methods have been utilized to compensate for variations in illumination. Among these are the FLD method described previously [Belhumeur 1997], illumination and pose manifold [Murase 1995], shape-from-shading [Zhao 2000], photometric alignment [Shashua 1997], quotient image [Shashua 2001], illumination cones [Georghiades 2001], and Lambertian reflectance and linear subspaces [Basri 2001].

1.2.2 Variations in Pose

Three Dimensional Modeling

Given a 2D facial image, an attempt is made to determine the location of specific points on the face such as mouth and iris locations. This information is then used to project the 2D facial image onto a previously constructed 3D model of the human face. Texture mapping techniques are employed to create a realistic 3D model of the head of the person in the 2D image. This 3D model can then be used to create a frontal 2D facial image. Illumination affects can also be accounted for in this modeling technique. Jebara shows some visually impressive results using this method [Jebara 1996].

1.3 Face Identification

The face identification problem is reduced to a classification problem if the normalization process has accomplished the stated goals. A simple nearest neighbor classification in face space is often used in conjunction with a PCA/FLD approach.

1.4 Neural Networks

The study and application of neural networks is a diverse topic. There are a plethora of neural network topologies and learning algorithms. As such it is beyond the scope of this discourse to cover them. The reader is referred to Dr. Genevieve Orr's website [Orr 1999] which has a straightforward introduction to neural networks including using neural network based PCA for compression of image data. Also, a Google search using the phrase "introduction to neural networks" will yield many basic tutorials on neural networks.

Neural networks have been applied to the face recognition problem in a variety of ways. As mentioned above, neural networks can be used to simulate PCA [Turk 1991]. Rowley, Baluja, and Kanade used a neural network in the detection process. A neural network was trained to give a positive response if a face exists in the portion of the image input to it. It was then scanned across the image in search of faces [Rowley 1998]. Since neural networks can be constructed as classifiers, they have been used as the classification method for the identification process. For example Er, Wu, Lu, and Toh used FLD as a dimensionality reduction then a radial basis function neural network for the identification classification [Er 2002]. Numerous other face detection and recognition algorithms have utilized neural networks.

2. FACE RECOGNITION SUBSYSTEM

Two major components of a family photo album face recognition subsystem where investigated, see Figure 2.1. Both the face detection module and the normalization module proposed where found to be insufficient to be utilized for a family photo album. The final identification module was never implemented, as the results from the previous two modules where insufficient to warrant attempting the identification process.

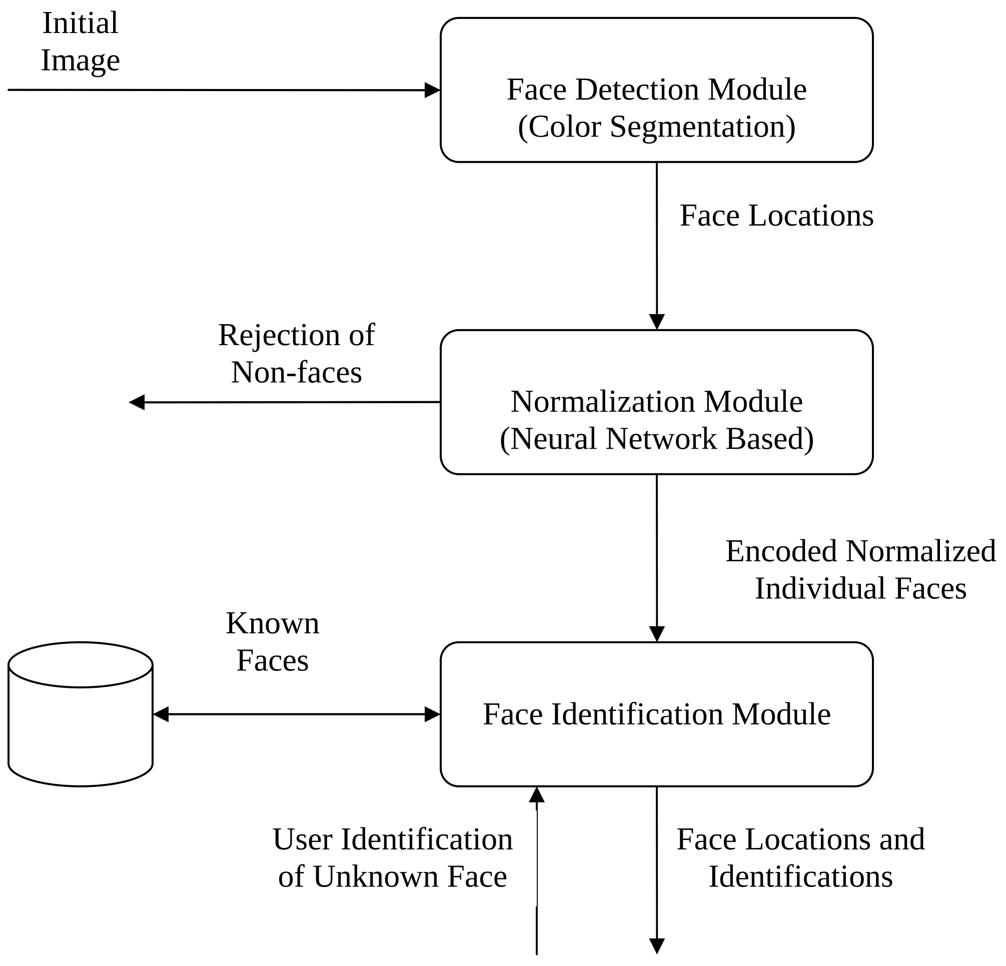

Initial Image
Face Detection Module (Color Segmentation)
Face Locations
Rejection of Non-faces
Normalization Module (Neural Network Based)
Encoded Normalized Individual Faces
Known Faces
Face Identification Module
User Identification of Unknown Face
Face Locations and Identifications

Figure 2.1 System Overview

2.1 Face Detection via Color Segmentation

The proposed face detection algorithm consisted of two steps. The first step was to utilize color information to determine which areas of the image contained human skin. The second step was to filter these areas based on shape and size to determine probable face locations. Multiple segmentation criteria where utilized in this process, however none was found to be very effective. If the segmentation criteria where broad enough to get most of the skin regions in an image, large non-skin areas of similar color where also included. Using narrower segmentation criteria caused large portions of skin areas to be ignored. This resulted in single faces being split into multiple regions that where very difficult to identify as faces. Furthermore, filtering detected skin regions based on shape and size was not adequate to determine likely face candidates.

2.2 Normalization

The normalization process proposed training a neural network to perform a nonlinear principle component analysis of an image of a face. Figure 2.2 and 2.3 show the proposed configurations. The principle components created by this network could then have been used to simplify the identification process. However, a network could not be trained that performed the nonlinear principle component analysis. Many networks were able to learn to produce the desired output image for individuals that where used in the training process. However, no network was found that was able to reproduce images of an individual that was not part of the network training. This was true even when only frontal images with normal lighting where used. Interestingly, many networks learned very quickly to reproduce images of individuals in the training set. However, the results show more of a memorization process than the desired nonlinear PCA. A few of the largest networks trained showed indications of being able to reconstruct faces as would be expected if the desired nonlinear PCA where being performed. However, the reconstructed faces where not recognizable as the individual input to the network. Although this was encouraging, no network was able to progress beyond this point.

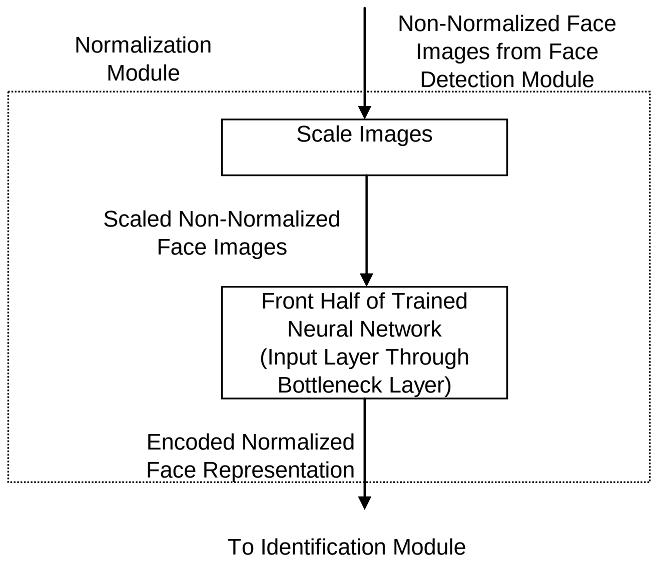

Normalization Module
Non-Normalized Face Images from Face Detection Module
Scale Images
Scaled Non-Normalized Face Images
Front Half of Trained Neural Network (Input Layer Through Bottleneck Layer)
Encoded Normalized Face Representation
To Identification Module

Figure 2.2 Normalization Module Block Diagram

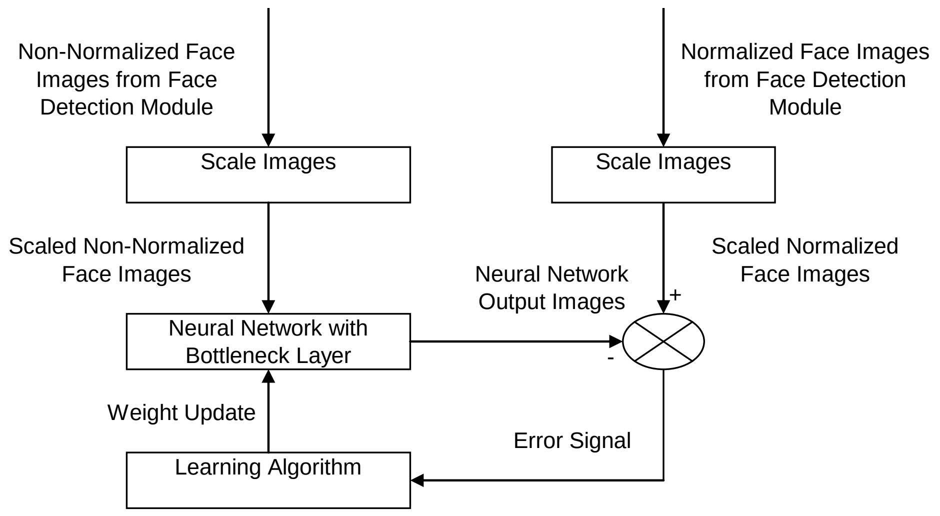

Non-Normalized Face Images from Face Detection Module
Normalized Face Images from Face Detection Module
Scale Images
Scale Images
Scaled Non-Normalized Face Images
Scaled Normalized Face Images
Neural Network Output Images
+
-
Neural Network with Bottleneck Layer
Weight Update
Error Signal
Learning Algorithm

Figure 2.3 Neural Network Training Overview

3. SYSTEM DESIGN

3.1 Language and Platform

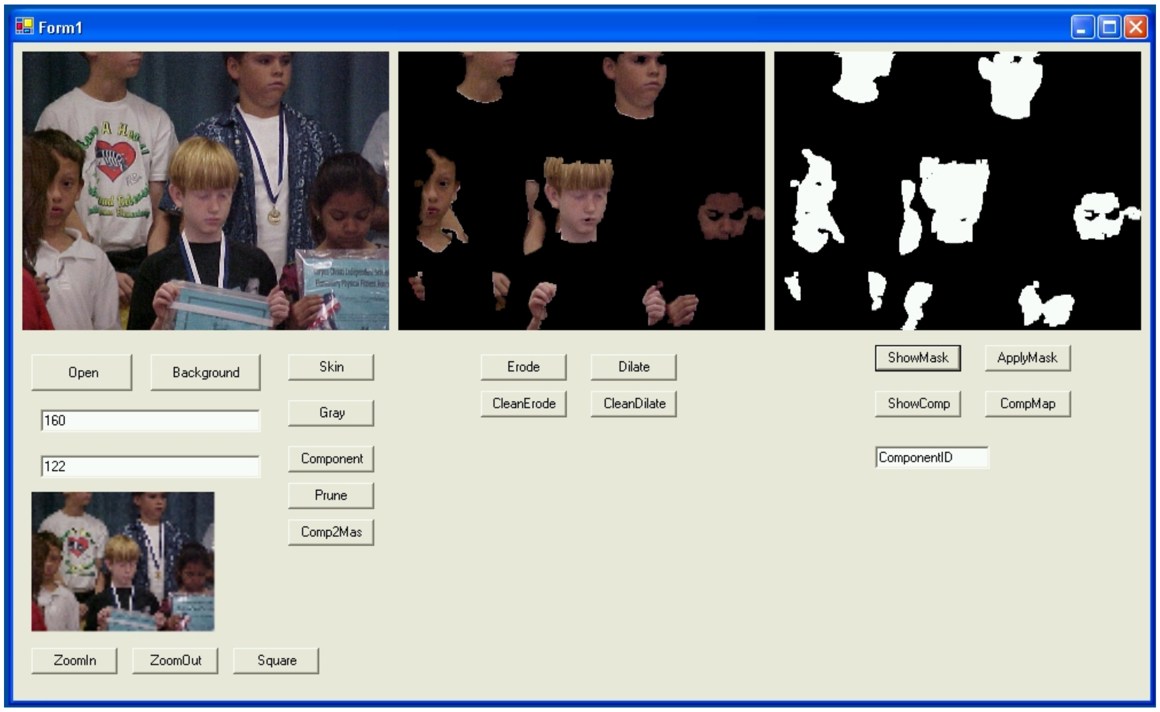
Both the face detection module and the normalization modules where implemented in Visual C++.Net using Microsoft Visual Studio .Net 2003. The entire process was performed on machines running Microsoft Windows XP. Three additional software packages where used. OpenCV, originally developed by Intel, is an open source computer vision library [Wikipedia 2007] and was used to perform face detection when it was determined that color segmentation was not sufficient. Microsoft Access and Microsoft Excel where also used at various stages.

3.2 Data Set

The CMU PIE data set consist of over 40,000 facial images of 68 people in 13 different poses, under 43 different illumination conditions, and with 4 different facial expressions [Sim 2002]. This image set was obtained directly from Carnegie Mellon University and contained images in the PNG file format. Prior to using the images a program was written to convert all the images to a bitmap format. This allowed the images to be read directly into Visual C++.Net using the built in Bitmap class.

3.3 Face Detection via Color Segmentation

The face detection module investigated consists of a three step process. First color segmentation was used to remove all pixels that are not skin. Secondly, erosion and dilation were used to clean the image. Finally, a component detection algorithm was used to identify each skin region. This module was implemented in a visual c++.net forms application which allowed each step to be visualized. The main window of the application displays three images. On the left hand side of the window the original image is displayed. The middle image displays the effect of various operations on the original image. The image on the right hand side of the window can be used to display the mask that will be applied to the image or the detected components. The main window of this application is shown in Figure 3.1. As this application was intended as a research tool to investigate the feasibility of face detection via color segmentation and not as a final application, the user interface is course and not particularly user friendly. This application requires the user to have a good understanding of the desired process.



160

122

ComponentID

Figure 3.1 Color Segmentation Application Main Screen

A basic c++.net forms application was created using Microsoft Visual Studio. The form design tools where used to add the various buttons and other controls. When the Open button is pushed and an image file loaded, a new frImage object is created. All the controls that perform manipulations on the images/mask do so by accessing member functions of the frImage object. The structure of the frImage class is shown in Figure 3.2.

frImage Class	
Private Attributes	
bmpOriginal	Bitmap
bmpFiltered	Bitmap
bmpComparison	Bitmap
mask[,]	UInt32
compMap[,]	UInt32
Components	SortedList of frComponents
height	int
width	int
Public Member Functions	
MakeGray	
SkinDetect	
Dilate	
Erode	
eclean	
dclean	
ComponentDetect	
ShowComponent	
ComponentPrune	
Mask2Comparison	
Comp2Comparison	
Comp2Mask	
Comparison2Mask	
ApplyMask	
Private Member Functions	
AddComponent	
MergeComponents	
AddPixel	
RemoveComponent	

frComponent Struct	
id	unsigned int
xmin	int
xmax	int
ymin	int
ymax	int
area	unsigned int

Figure 3.2 frImage Class and frComponent Structure

3.3.1 Color Segmentation

Color segmentation consists of comparing the color of each pixel in the original image with a predefined range of colors that are considered skin. If the pixel falls in this range of colors the pixel is considered to be skin. The mask is an integer array of the same dimensions as the image. For every pixel in the original image designated as skin the numeric value of the color white is entered in the corresponding mask location. If the pixel in the original is not skin the numeric value of the color black is entered in the corresponding mask location. Thus, the mask results in a skin map of the original image. At this point a new image can be created using the mask and the original image. In the new image a pixel has the same value as in the original if the corresponding mask value is white. Otherwise, the pixel in the new image has a color value of black. Figure 3.3 is representative of the results of this operation. The original image is shown on the left, the mask used is shown on the right, and the new image with only skin showing is in the center. Ideally, this new image would be black except where skin is present in the original image.

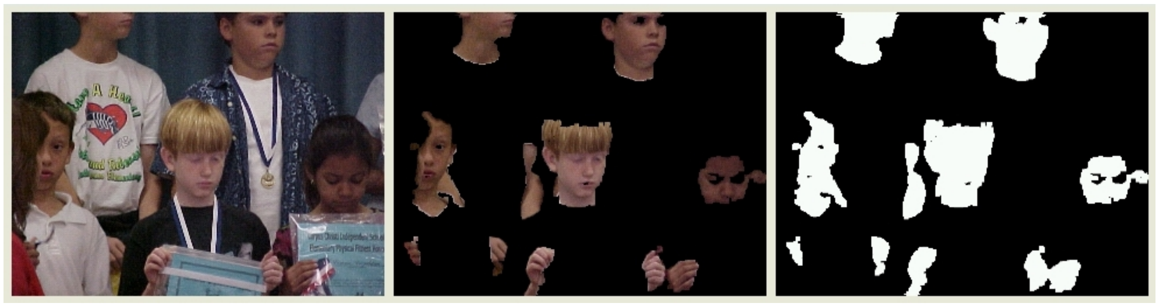


Figure 3.3 Color Segmentation Results

3.3.2 Erosion and Dilation

Erosion

It was observed that color segmentation often resulted in a large number of very small regions being labeled as skin. This was especially true if a surface in the picture was close to skin color. Figure 3.4 shows the mask before and after the erosion process. In this example, the erosion process removed a large number of small areas in the upper right quadrant of the image. The erosion process removes a layer of pixels around the edge of every region. This results in small regions being removed and can significantly reduce the number of regions.

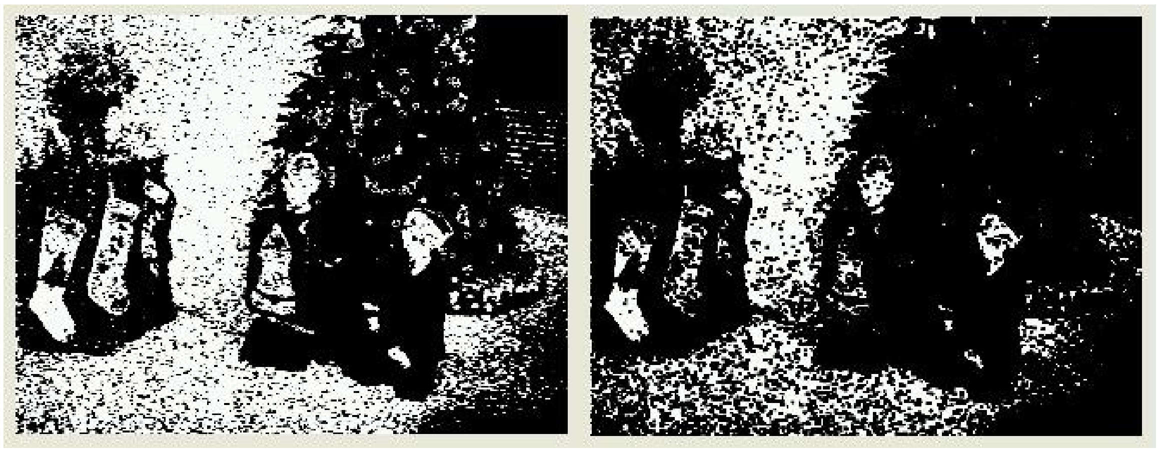


Figure 3.4 Erode Example

The erosion algorithm implemented was broken into two steps too clarify the effect of the erosion process. The first step was to mark every pixel that would be eroded with yellow. This process is performed when the user presses the Erode button. The second step is to convert all the yellow pixels to black. This is performed when the user presses the CleanErode button. The erosion algorithm steps through the mask looking for a pixel that is on. That pixel is then changed to yellow if any pixel a distance of k/2 or less in either of the horizontal or vertical directions is off. In this computation k represents the size of the erosion and was set to five (5) in the application.

Dilation

The dilation process is the opposite of the erosion process and is intended to fill in holes in detected skin regions. The dilation process adds a layer of pixels around the edge of detected skin regions. The dilation algorithm implemented was also divided into two steps so that the effects could be visualized. Every pixel that was to be added through the dilation process was first marked in red on the mask. This was accomplished by stepping through the mask until a pixel is found that is off. That pixel is changed to red if any pixel a distance of k/2 or less in either of the horizontal or vertical directions is on. In this computation k represents the size of the dilation and was set to seven (7) for this application.

3.3.3 Component Detection

Component detection is the process of grouping detected skin pixels into regions called components. These components are then labeled, stored in a sorted list and a component map is created. The component map can then be used to visualize the component detection process. Ideally, the sorted list of components could be further processed to determine if faces where present or forwarded to the normalization module.

Figure 3.2 shows the frComponent structure used to implement component detection within the frImage class. The member functions of the frImage class related to component detection are ComponentDetect, ComponentPrune, AddComponent, MergeComponents, AddPixel, and RemoveComponent. In addition, to the frComponent structure show in Figure 3.2, frImage has two other data members related to component detection. Components is a SortedList of components and would be passed to the normalization module. The second data member is compMap and is a Uint32 array the same size as the original image. For every pixel in the mask that is on, compMap will contain an identifying number that indicates which detected component this pixel belongs to.

The ComponentDetect member function creates both the Components SortedList and the compMap component map. It starts by stepping through the mask array from left to right and top to bottom until a pixel is found to be on. As shown in the flowchart in Figure 3.5, when a pixel is found that is on, the neighboring locations shown in Figure 3.6 are examined. The first possibility is that none of the neighboring locations are on. In this case AddComponent is going to be called to add this pixel as a new component. It will be given the next available ID number and the algorithm will proceed to the next pixel in the mask array. The second possibility is that one or more of the neighboring locations were already labeled as a component. In this case the location is added to the first neighbor that was found using AddPixel. However, at this point it is possible that another neighbor contained a different ID value. This would indicate that these two components are connected via this pixel & thus should be merged into one component. This is accomplished by calling MergeComponents for any neighbors that do not have the same ID as the current pixel. This entire process is shown graphically in Figure 3.6.

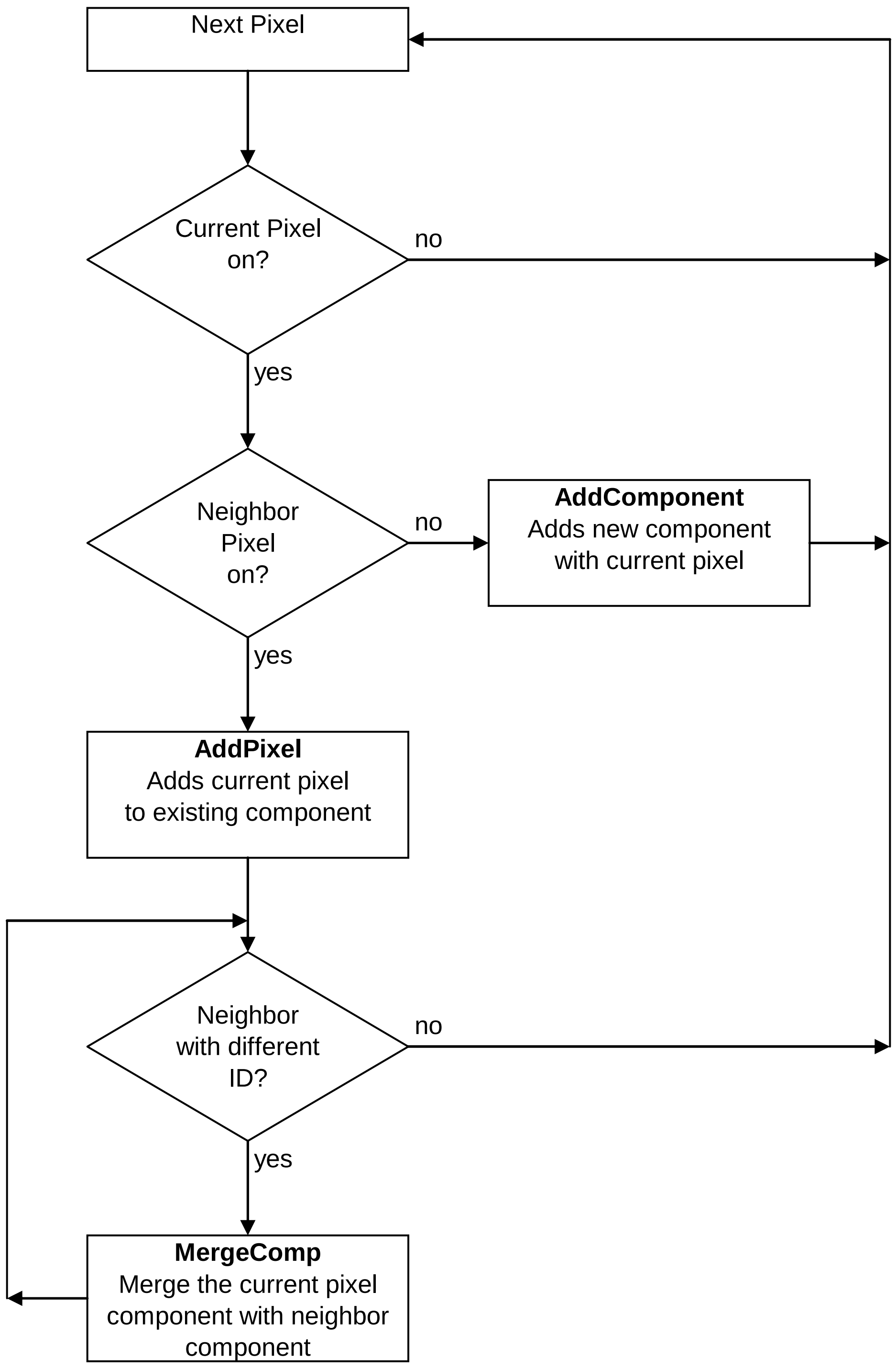

Next Pixel
Current Pixel on?
no
yes
Neighbor Pixel on?
no
AddComponent
Adds new component with current pixel
yes
AddPixel
Adds current pixel to existing component
Neighbor with different ID?
no
yes
MergeComp
Merge the current pixel component with neighbor component

Figure 3.5 ComponentDetect Flow Chart

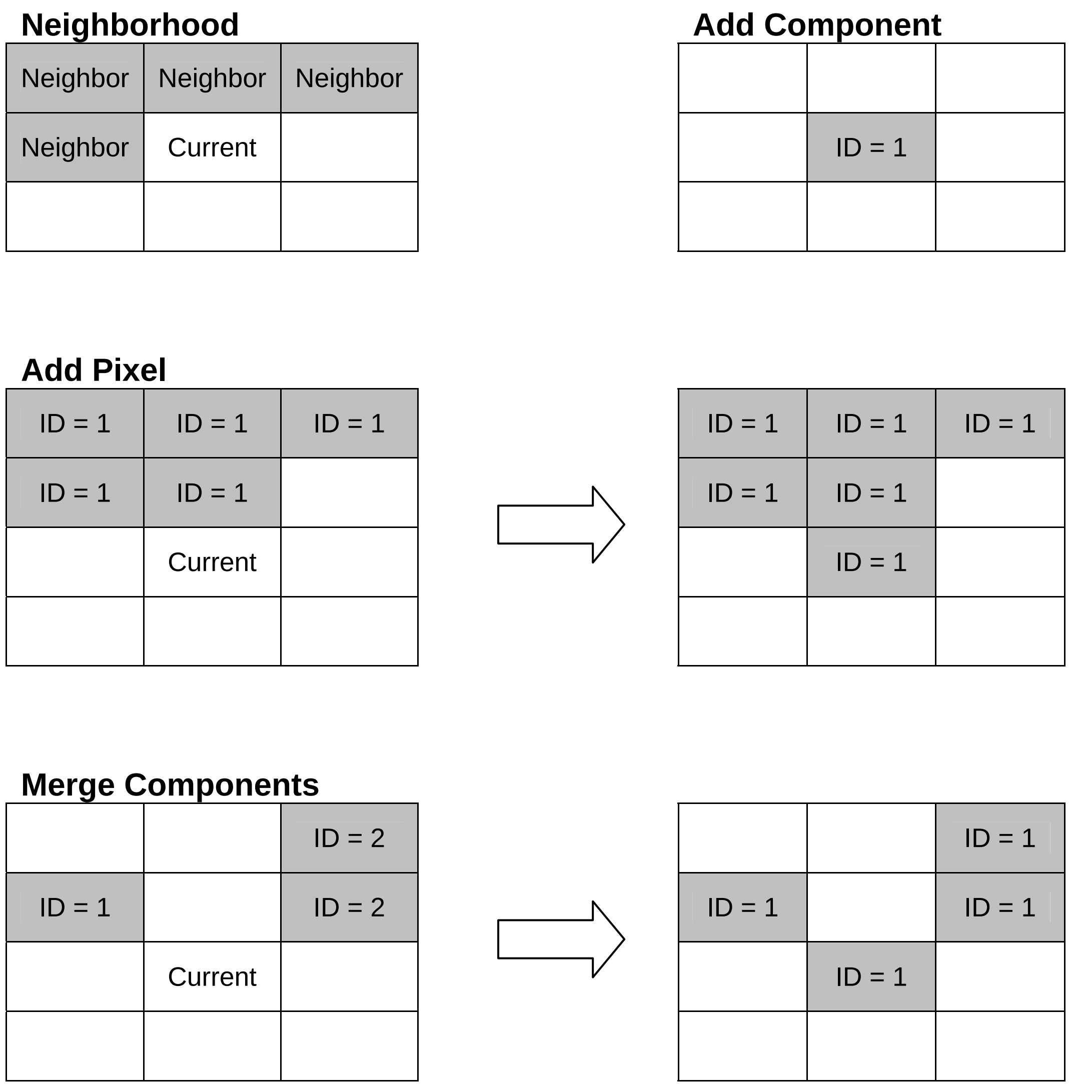


Figure 3.6 Component Detection Scenarios

3.4 Normalization Module

The normalization process is supposed to facilitate the recognition process by eliminating factors in the image not related to the person’s identity. Ideally, the normalization process would remove variations do to lighting, pose, expression etc. The normalization algorithm investigated in this study was based on a neural network being able to learn to perform a nonlinear PCA type dimensional reduction of face images. The network was expected to create a dimensionally reduced representation of a normalized face when given a non-normalized input face. For this to be successful a neural network with a bottleneck layer must be trained to produce a normalized image of an individual when given a non-normalized image of that same individual. Furthermore, such a network must demonstrate the ability to combine features and create a new face when presented with an individual not in the training set.

Training such a network required picking a normalized image for each individual and using this as a target when the network was presented with any image of this individual. Creating such training sets involved three steps. First the faces were detected using a program called FaceDetect. Then the desired images for a given training set were selected using a Microsoft Access database. Finally a program named DisplayFaces was used to create training sets for the neural network.

3.4.1 Face Detection to Create Training Sets

A reliable face detection algorithm was required to create usable training sets for the neural network. As the face detection via color segmentation algorithm did not perform adequately, the OpenCV library was used to create a face detection application. The OpenCV library is an open source C library for computer vision. It has a face detection algorithm based on a cascade of boosted classifiers using Haar like features [OpenCV 2007]. The application FaceDetect steps through a list of images utilizing the OpenCV library to detect faces in each image. It then creates a CSV (comma separated values) file containing the location of each face detected. From the original CMU PIE database images, only images where the persons was facing within 45 degrees of forward where passed to the FaceDetect program. This results in about 23000 locations being labeled as faces.

3.4.2 Image Selection for Training Sets

The CSV file created by FaceDetect was imported as a table in Microsoft Access. Figure 3.7 shows the structure of this table. The face detection process produced numerous false detections. These had to be removed for the proposed neural network training. Rather than sort through all these images by hand, it was decided to remove face locations based on deviation from means. Since the CMU PIE database contains multiple images of each individual from each camera and these images where taken very rapidly with the subject sitting still, the location of the face for any given individual and camera should be close across multiple images.   A query was created in Microsoft Access to calculate the standard deviation in the location and size of the detected faces for a given individual and camera. A second query was then used to eliminate detected regions that where outside a given number of standard deviations. This allowed many of the false detections to be removed from the training set. The results of this query where then exported to a csv file.

	FacLoc	
PKID	Autonumber	Primary Key
File	Text	Complete File Name
ID	Text	Individiuals ID
Type	Text	Image Type
Cam	Text	Camera
Face	number	Detected Face Number
x	number	Upper Lefthand Corner x
y	number	Upper Lefthand Corner y
w	number	Width
h	number	Height

Figure 3.7 MS Access Table Structure

The csv file exported from MS Access contained the image file name, the ID of the individual, the image type, the face number, two integers specifying the x and y location of the upper left hand corner of the face, and two integers specifying the width and height for each face in the set. This file was then read by a program named DisplayFaces. This program allowed each image listed in the csv file to be viewed with a box around the detected face. The detected faces could then be manually removed from the training set by clicking the remove button. After removing all false detections the DisplayFaces application crops and scales the detected faces and combines them into a neural network training (nnt) set file. The format of this binary file is shown in Figure 3.8.

NNT File	
Header	
Number Images	int
Width of Each Image	int
Height of Each Image	int
For Each Image	
Full Path and File Name	String
Grayscale Bit Values	unsigned char

Figure 3.8 Neural Net Training File Format

3.4.3 Neural Network Design

The design of the neural network was based on the standard back propagation of errors algorithm and was implemented as a c++ class. Figure 3.9 shows the major features of the class and the two support classes NNRnd and Sample. The private member structure of the NeuralNet class, Layer, is also shown. The NNRnd class simply encapsulates the random number generator in visual c++ and provides methods to return various ranges of random numbers. The Sample class provides simplified input and output options to the neural network. It stores arrays of input and output pairs and can be passed directly to the training and execution routines in the NeuralNet class. Appendix B describes the testing of these classes and some samples that indicate the correctness of the implementation.

NeuralNet Class	
Private Attributes	
Nlayers	int
layer	array of Layer objects
Err	double
Desc	String
TrainIter	int
sfi - scale factor	double array
sfo - scale factor	double array
…	
Public Member Functions	
Execute	
GetTrainIter	
Train	
Scale	
LearnRate	
LearnRateAdjust	
RandWeight	
Save	
Load	
Private Member Functions	
FeedForward	
BackProp	
WeightUpdate	
MSE	
SaveScale	
LoadScale	
SaveLayers	
LoadLayers	
SaveWeights	
LoadWeights	
LoadInputs	
LoadTarget	
ScaleOutput	
ResetDeltas	
sigmoid	

NNRnd Class	
Private Static Attributes	
RndNum	Random (Object)
Public Static Member Functions	
Char	unsigned char
Double	double
PlusMinusOne	double

Sample Class	
Public Attributes	
Inp	unsigned char array
Outp	unsigned char array
Description	String
ID	String
InpWidth	int
InpHeight	int
OutpWidth	int
OutpHeight	int
Public Member Functions	
Sample	
CreateSample	
GetSample	
SetDescription	
SetSize	
Randomize	
PrintSample	
PrintPairs	

Layer Struct	
ID	int
NNodes	int
Out	double array
Targ	double array
Err	double array
W	double array
Wsaved	double array
dW	double array
pdW	double array
LR	double
MR	double

Figure 3.9 NeuralNet Class and Support Classes

Layer Struct

The Layer struct is a private member of the NeuralNet class. This structure contains the pertinent information about a layer of the network. Basic information such as the number of nodes in the layer, the most recent output of each of those nodes and the weights from each node in the previous layer to each node in the current layer is stored in this structure. This structure also stores information related to the learning process such as the error gradient associated with each node, the current and previous delta associated with each weight, and the learning and momentum rates for the layer. The weights stored in Layer are from nodes in the previous layer to nodes in the current layer. Thus, the input layer does not have any weights. Layer also stores target outputs for the output layer. These are not used in the other layers.

NeuralNet Class

The NeuralNet class encapsulates the functionality for setting up the neural network, scaling the input and output, training and executing the network, and saving and loading the network. As shown in Figure 3.9, the NeuralNet class contains an array of Layer's. It also contains integers to indicate the number of layers in the network and the number of training iterations performed. The first step in creating a neural network using the NeuralNet class would be to call the constructor. After creating the NeuralNet object, scale factors could be set using the Scale member function. The network is then ready to train using one of the Train member functions. After training, one of the Execute member functions can be used to validate the training process. The network can also be saved to and loaded from disk using the Save & Load member functions.

NeuralNet Constructor

The NeuralNet constructor creates a network with random weights, given an array of int's indicating the number of nodes per layer. Thus, if an array of ints containing the values {5, 3, 2, 1} was passed to NeuralNet, a neural network with 4 layers, 5 inputs and 1 output would be created. This network would have two internal layers with 3 and 2 nodes respectively. Internally, this is accomplished by calling the Create function which initializes all memory necessary and sets all initial values.

Scaling Input and Output

Scaling the input and output of a neural network helps prevent saturation and is a widely used technique to improve network performance. The Scale member function simplifies this process by determining the appropriate scaling for each input and output and applying this scaling as needed. To enable scaling, the user needs to call the Scale member function. This function takes 4 arrays of double precision numbers. The first two arrays are the same length as the number of input nodes and indicate the minimum and maximum possible values of these inputs respectively. The second two arrays are the same length as the number of output nodes and likewise indicate the expected minimum and maximum range of each output. The Scale member function uses these arrays to calculate a set of linear scaling factors for each input and output. A flag is then set indicating scaling is in effect. Once this flag is set any inputs sent to the network are scaled prior to applying them to the network. Also, any network outputs are scaled back to the original range prior to returning them to the user.

Training

There are two overloaded member functions called Train which can be used to train the neural network. The only difference in the two functions is the format of the training and testing samples. One function requires an array of Sample objects for each of the training and testing samples. The other requires an ArrayList object which contain Sample objects for each of the training and testing samples. Both functions also require an integer indicating the maximum number of training iterations to process. The Train function starts by passing each Sample from the test set to the network and determining the cumulative error on the test set. This error will later be used to determine if training has improved the network and to save the weights that performed the best on the test set. The training iterations proceed as follows:

```
For each Sample in the train set:
    Pass the Sample through the network.
    Back propagate the errors from the target output.
    Update the network Weights if non-epoch training.
Update the network Weights if epoch training.
For each Sample in the test set:
    Pass the Sample through the network.
    Cumulate the test error.
If the test error is less than the previous test error, then store the weights
```

After completing the prescribed number of training iterations, the weights that performed the best on the test set are re-loaded and the network is saved to disk.

Execute Member Functions

There are 5 overloaded member functions named Execute. They each pass a given input Sample or set of input Samples’ through the neural network to produce an output. The first two overloads receive a set of inputs via an array and produce an array containing the network output. These two do not require a target output and thus do not return the error of the network. They also only work with one set of inputs and outputs per call. The next 3 overloads of Execute do return the error of the network based on a given target. These 3 overloads receive either an array of Sample objects or an ArrayList containing Sample objects. They execute each sample in turn and return the cumulative error over the entire sample set. For the error returned to have meaning, each Sample object must contain the target output corresponding to its input array. The other variations in the overloads pertains to where the network output is stored and if it overwrites the target output with the actual network output.

Save and Load Member Functions

Finally, the Save and Load member functions can be used to save and load the neural network to and from disk. These functions accept an open FileStream object. The Save member function writes the number of training iterations, the number of layers, and the number of nodes in each layer to the FileStream. It then writes all the scale factors for the network and all the weights for each layer to the FileStream. The Load member function reads this exact same information. The current NeuralNet object is then re-created using this information. If the number of nodes in each layer or the number of layers read from the FileStream differs from the original NeuralNet object, Load returns False otherwise it returns True. However, in either case the current NeuralNet object is adjusted to match what was read from the FileStream.

3.4.4 Training Console

A c++.net application named TrainingConsole was created to train various neural network configurations on the previously created training sets. This application is a console application rather than a windows forms application. The name of a configuration file is passed to this application from the command line. The format of this text file is shown in Figure 3.10. The splits file referenced is a comma separated values (csv) file with each line containing an individuals ID and an integer representing which set (train = 1, test = 2, or validation = 3) this individual belongs to. The TrainingConsole uses the information in the configuration file to train the specified neural network on the specified training images.

NNC Text File	
Line #	**Description**
1	Training Set File Name (.nnt file)
2	Target Set File Name (.nnt file)
3	Splits File Name (.csv file)
4	Number Training Iterations per call
5	Network Configuration (1024_10_1024)
6	Input Image Width
7	Input Image Height
8	Output Image Width
9	Output Image Height

Figure 3.10 Neural Network Configuration (.nnc) File

The TrainingConsole application uses the splits file to divide the images in the training file into three sets. The train set is used to update the weights of the neural network via the back propagation algorithm. The test set is used as a stopping condition for the training. The validation set is used to verify the success of the networks learning. The splits file is used to associate each individual with one of these three sets. Each individual in the training file has an entry associated with their ID in the splits file. This entry specifies which set their images belong to. The three sets are stored in ArrayLists of Sample objects.

After the images in the training file are divided into sets, TrainingConsole begins the training process. The ArrayLists containing the train set and the test set are passed to the Train member function of NeuralNet and the network is trained for the specified number of iterations. Recall, this member function saves and reloads the weights that performed the best on the test set during the training process. After the prescribed number of training iterations, each of the train, test, and validation sets are passed to the trained neural network. For each of these sets, the input images, target output images, and neural network output images are written to files to be read by the application ResultsViewer. A flag file is then read from the default output directory. This file is the users' only interaction with TrainingConsole while it is running. If the first character of the flag file is anything other than a 'd' for 'decrease' or a 's' for 'stop' the training continues for another set of iterations. If the first character of the flag file is a 'd' for 'decrease' then the learning and momentum rates are decreased and the training continued for the specified number of iterations. If the files first character is a 's' for 'stop' then the training stops and the program saves the best network found so far.

3.4.5 Viewing the Results

The output from the TrainingConsole program was read into a Windows forms application called ResultsViewer. This application displays the input, target output, and neural network output images side by side so that comparisons can be made. This program also converts the resulting comparison images into a bitmap that can be saved to file.

3.4.6 Neural Network Training

Multiple feed forward neural networks where trained using the back propagation of errors algorithm with a momentum factor in an auto-associative configuration. The networks included a hidden layer with a small (less than the number of individuals in the training set) number of nodes. This configuration is known to be capable of performing the desired PCA [Turk 1991]. A training set was created that only included one face for each individual. The face included was forward facing, normally illuminated, and with a neutral expression. The 68 individuals in the CMU PIE database where divided into the train set, the test set, and the validation set. The train set was used with the back propagation algorithm to update weights. The test set was used as the early stopping criteria to prevent overtraining. The validation set was used in the final comparison of multiple networks. Multiple network configurations where then trained using epoch learning. When this failed to produce the desired results, the learning algorithm was changed so that weight update took place after each sample presentation. As the trained networks where never able to learn the desired behavior on this simple training set, more difficult training sets where never presented. However, many modifications as to the individuals in each of the train, test, and validation set where attempted. Also, for validation of the process, networks where trained using only a single individual.

4. EVALUATION AND RESULTS

4.1 Face Detection via Color Segmentation

Color segmentation was found to be insufficient to detect human faces in realistic photographs. The method was deficient in three main areas. First, if the images had background areas that where close to skin colors, large areas of the photo would be selected as ‘skin’. In some cases the areas where so large that multiple faces would be considered a single skin region. This is demonstrated in Figure 4.1. The image on the left is the original image. The image on the right is the component map showing the detected components. The middle image shows the effect of applying the component map as a mask to the original image. The second obstacle to using color segmentation for face detection was its susceptibility to variations in lighting color. In the case of the CMU PIE database apparently the blue content of the flashbulbs used resulted in very little skin being detected. Figure 4.2 shows an image from the CMU PIE database with both natural lighting and a flash. In fact, in almost all of the CMU PIE images where a flash was used very little skin was detected. The final issue with using color segmentation to detect faces involves selecting discontinuity in the detected region. Because of the inability of the color segmentation to detect skin pixels and only skin pixels, the actual face region is often segmented into multiple regions as shown in Figure 4.3. There is no reliable way to know when to combine these regions and when these regions represent separate faces.

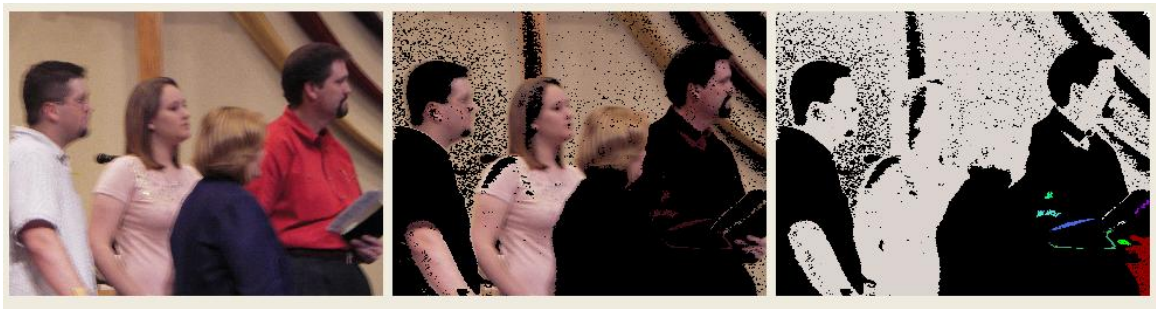


Figure 4.1 Multiple Faces in a Single Component

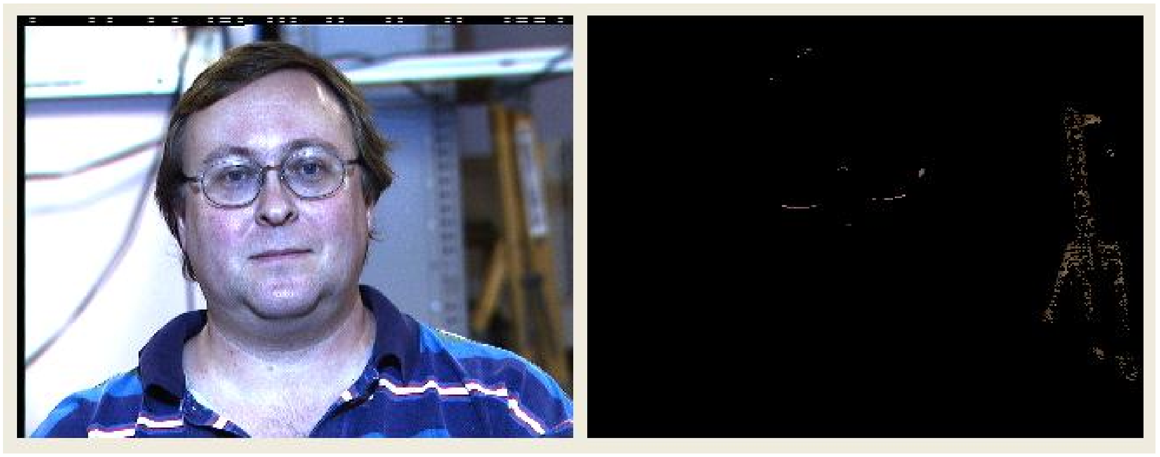


Figure 4.2 Lighting Effect on Skin Detection

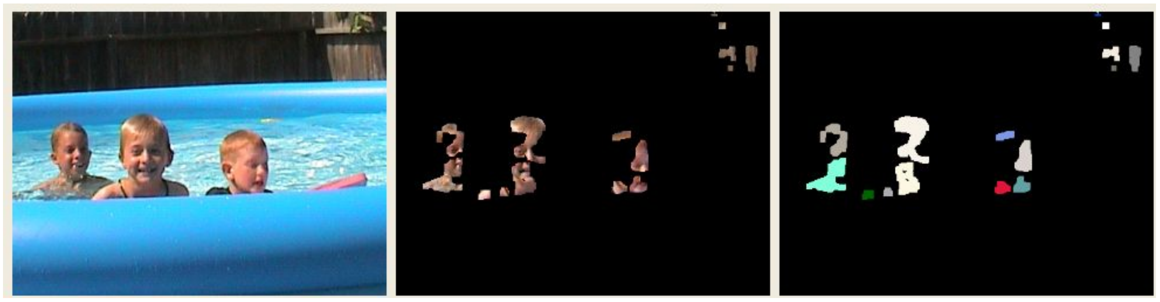


Figure 4.3 Multiple Components per Face

4.2 Neural Network

4.2.1 Concept Test – Single Individual Training

A simple training set was used to verify the NeuralNet class and algorithms and to show the plausibility of the method. In this case a neural network was trained to reproduce a single individual. Figure 4.4 shows the train and test sets for this case. The three columns of images represent the input image, the target image and the neural network output image respectively. It is interesting that the simplest possible network with the required number of inputs and outputs was capable of learning this mapping. For a 32 x 32 bit input image, a network with 1024 input nodes, 1 hidden node, and 1024 output nodes (here after abbreviated 1024 x 1 x 1024) was capable of recreating the input image at the output. It took less than 10,000 training iterations to learn this mapping. This indicates that the algorithm developed is capable of learning to produce a face image. It is also indicative of the correctness of the developed applications.

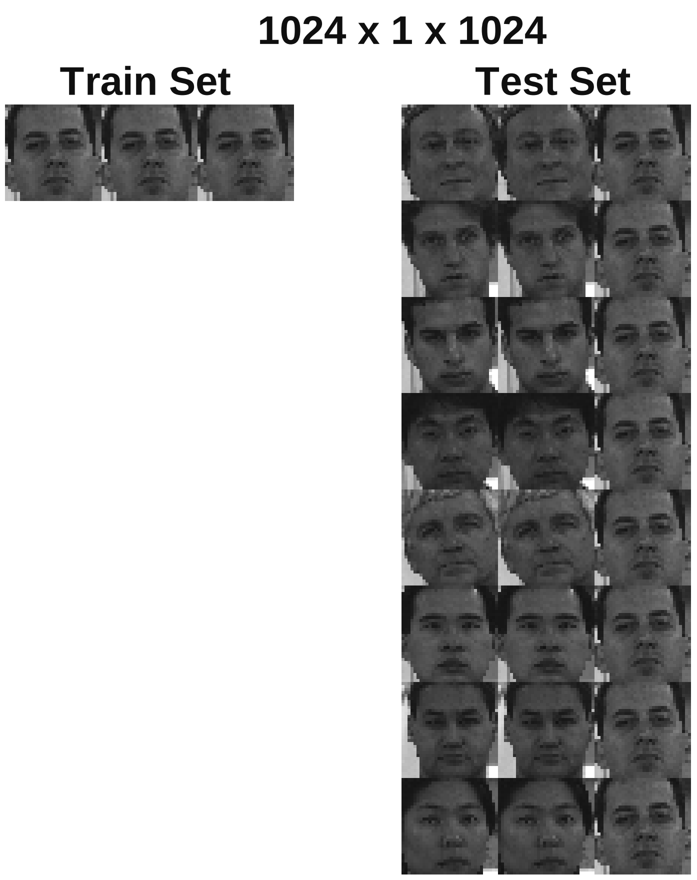


Figure 4.4 Single Individual Train Set

4.2.2 Epoch Training

When epoch training was used networks quickly learned to create an ‘average’ face. This ‘average’ face was then the output for any input given. When a face from any of the three sets (train, test, or validation) where input to the networks trained this way, this same ‘average’ face was output from the network. After this discovery all further training was without epoch weight update.

4.2.3 One Image of Each Individual

The next training set investigated involved one image of each individual. The neutral image (forward facing, natural lighting, neutral expression) of each individual was used as both input and target output. This set consists of 68 images and was divided into train, test, and validation sets. After eliminating epoch training, multiple networks where found that where capable of learning the individuals in the train set. Figure 4.5 shows portions of the train set and the non-train sets. Restrictions on the publication of images in the CMU PIE database prevent the entire sets from being presented. The results shown are typical of such a network. As is shown in Figure 4.5, these networks did not perform very well on the test and validation (non-train) sets. On these sets the network typically output an image of one of the individuals from the train set. To be considered successfully performing the desired PCA type combining of faces a network would have to demonstrate the ability to output a face recognizable as that of the person input to the network when presented with a face not present in the training set. Interestingly, it was observed that the number of individuals the network could learn was roughly the same as the number of hidden nodes for networks with a single hidden layer. Figure 4.6 shows the results of a 1024 x 5 x 1024 network trained on 9 individuals. Notice there are only about 5 distinct faces output by the network. This indicates the network was performing more of a memorization than a PCA type computation.

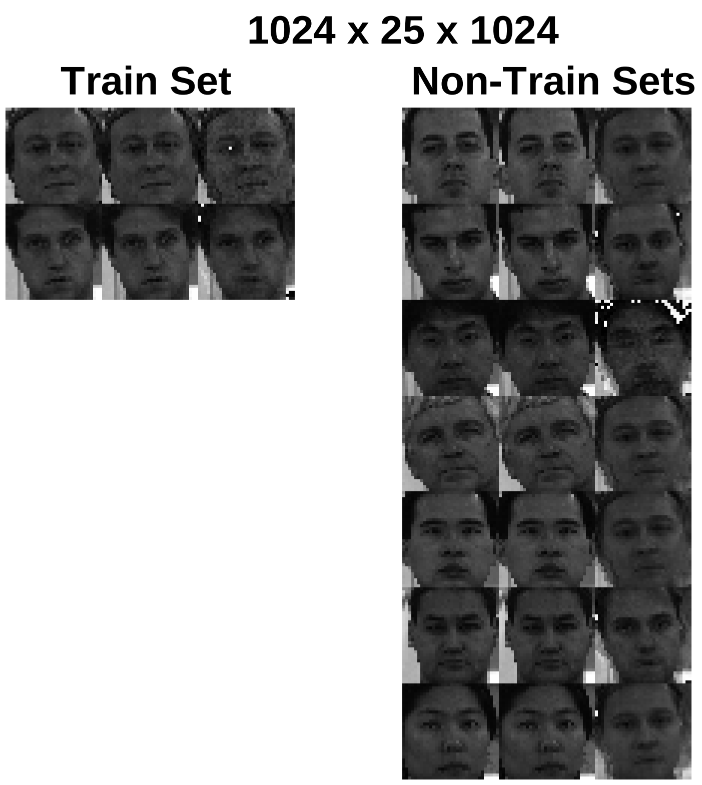


Figure 4.5 Typical Trained Network Results

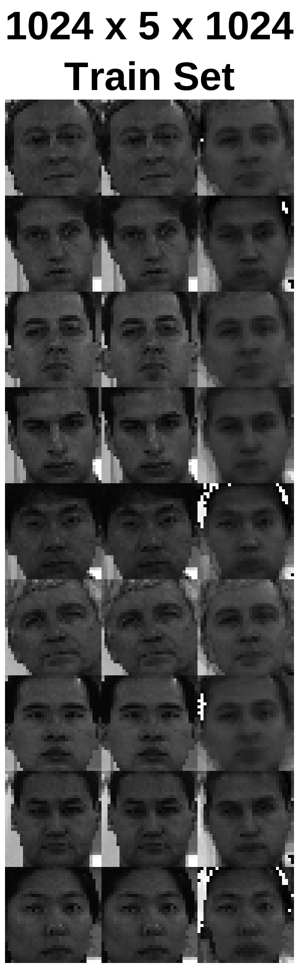


Figure 4.6 Trained on 9 Individuals

Only the largest networks were found to produce results similar to those expected from a PCA type analysis. A network with 300 hidden nodes was trained for over 393,000 training iterations. This training took over 4 weeks on a high end Pentium D processor. Some of the results of this training can be seen in Figure 4.7. Unfortunately, restrictions on the use of the CMU PIE database prohibit displaying all the faces. However, the important result is that some of the faces the network output on the test and validation sets were faces not output in the train set. This indicates that the network has some ability to create combinations of faces and features. It is this ability that is required for the network to be useful in the face recognition subsystem. However, the success of this network was very limited. Although not apparent from Figure 4.7, the vast majority of the faces output where unrecognizable. Even the faces that where indicative of the ability to combine where not recognizable as the person input to the network.

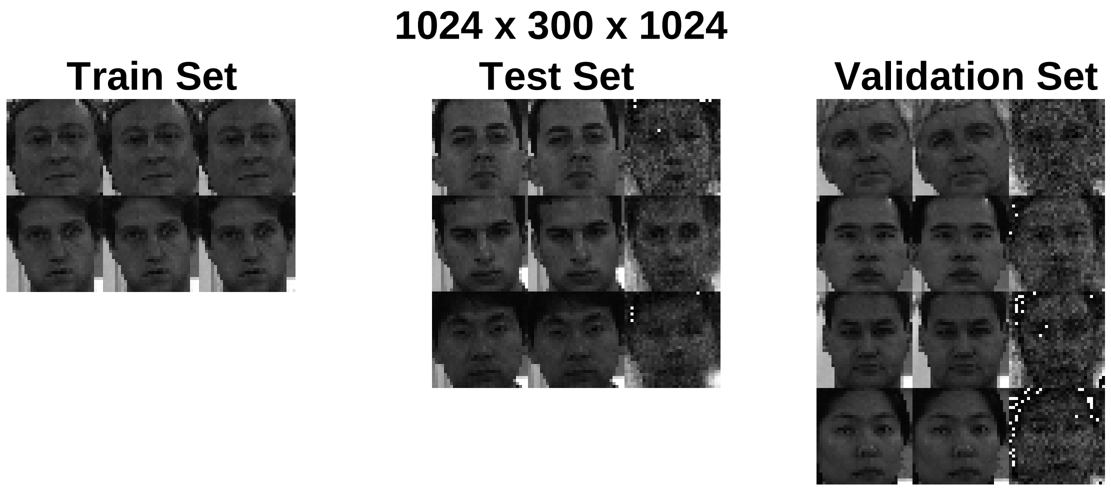


Figure 4.7 Large Network Results

Three additional large networks where trained in the same manner as the 1024 x 300 x 1024. These networks included two additional hidden layers around the bottleneck layer. According to [Bryliuk 2001] these additional layers should allow the network to represent the nonlinear data with fewer "Principle Components". Thus, the bottleneck layer should not need to be as large. The three networks trained had 25 nodes in the bottleneck layer. The additional hidden layers consisted of 100, 125, and 300 nodes. The resulting networks performed similar to the 1024 x 300 x 1024 shown in Figure 4.7. Interestingly, the 1024 x 300 x 25 x 300 x 1024 network took less time to train then the smaller 1024 x 300 x1024 network. This larger network converged in about 30,000 training iterations.

4.2.4 Multiple Images of Each Individual

The final training set used consisted of multiple images of each individual. The forward facing, neutrally lit, talking, images from the CMU PIE dataset where used as inputs. The target image for each individual was their neutral image. Networks trained on this training set performed better than the large network trained above. Indications of the ability to combine facial features where visible in the network output as shown in Figure 4.8. However, the network output was still not recognizable as the person input. In fact only a few of the output images demonstrated the desired combining of features. Most of the images output on the test and validation sets where clearly the same image output for an individual in the training set. For example, in the test set in Figure 4.8 consider the images of the two gentlemen with glasses in the eight and ninth row. The network output the same face for each of these gentlemen and the same face was present in the network output on the full training set.

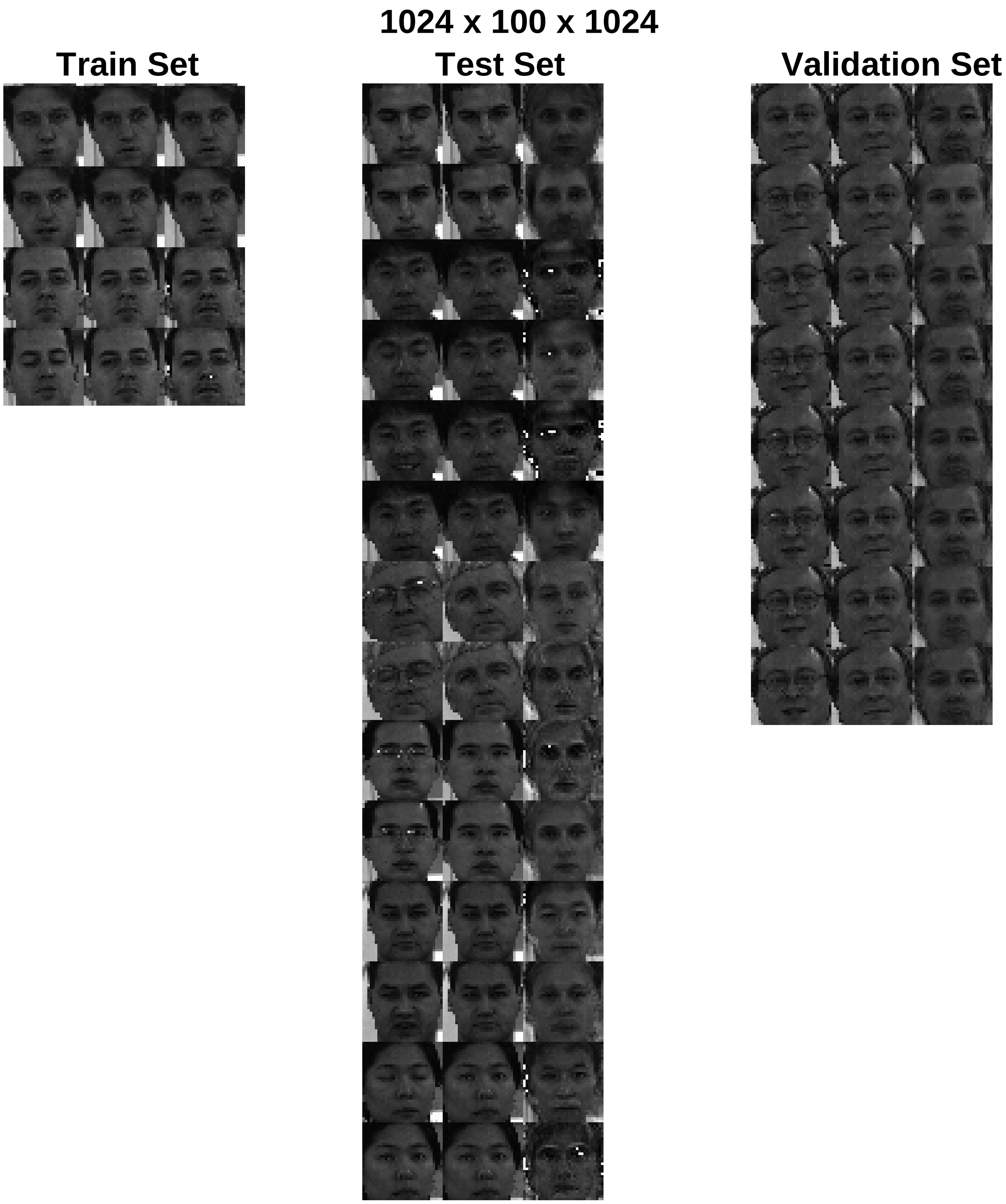


Figure 4.8 Network Trained on Multiple Images of Each Individual

5. FUTURE WORK

5.1 Face Detection

Face detection via color segmentation seems to hold very little promise when compared with the cascade of boosted classifiers using Haar like features method used in OpenCV. The pitfalls of the color segmentation concept seem unlikely to be overcome and thus do not warrant further investigation. However, the OpenCV method is far from perfect and research into new face detection methods will need to continue if automated face detection is to be reliable.

5.2 Neural Network Based PCA

Although the CMU PIE database had many images of each individual taken in very well controlled conditions, the database only contains 68 individuals. Training on similar images with more individuals may move the networks from a ‘memorization’ mode to a PCA type combination of facial features.

Future work should concentrate on larger neural networks, since the larger network showed some promise in being able to perform a PCA type combination of faces. However, the computational intensity of performing a thorough investigation using large networks with a sufficiently large training set is daunting. Although Turk and Pentland indicate a three layer network with a bottleneck layer is capable of performing the desired PCA functions [Turk 1991] others suggest a five layer structure is better suited for nonlinear data. Specifically, DeMers and Cottrell indicate that adding an additional hidden layer on either side of the bottleneck hidden layer allows the network to better represent nonlinear data with fewer “Principle Components”. They refer to the additional layers as encoding and decoding layers [DeMers 1993]. Although a few networks with five layers where trained, a more extensive search with a fuller dataset may be productive. Likewise, improved training methods such as the variable learning rates presented by Bryliuk and Starovoitov should be explored with a large face dataset [Bryliuk 2001].

5.3 Additional Possible Focus Areas

In addition to the direct continuation of this work, several interesting concepts were briefly explored which could be productive in this area. Many of these relate to the discovery that neural networks in the proposed configuration where very good at memorizing individuals. Although this ability did not directly fit with the proposed system design, a system designed around this ability may prove productive. For example a system could be designed were the end user actually trained a network on their individual family. This network should be capable of identifying individuals it has been trained on. Likewise, if a network is trained to reproduce a group of individuals and is feed an individual not in the group, would the network output the person who looks the most like the one input?

6. CONCLUSIONS

Despite the numerous applications for face detection and recognition, the current methods are far from perfect. Thus, research will need to continue in this area if these applications are to become commonplace. At this time a functioning face detection and recognition subsystem suitable for a family photo album was not attainable using the proposed system.

6.1 Face Detection via Color Segmentation

The color segmentation schemes investigated involved determining if each pixel in a picture was ‘skin’ based on its color. Manipulations where then performed to group these pixels for face detection. This method was very susceptible to color variations caused by lighting, background, and skin color. It was found that other methods that don’t rely on color where more capable of detecting faces in varying conditions.

6.2 Neural Network Based PCA

To be considered successfully performing the desired PCA type combining of faces a network would have to demonstrate the ability to output a face recognizable as that of the person input to the network when presented with a face not present in the training set. If a neural network can be found which performs such a nonlinear PCA style combining of faces and facial features it would be a very effective method of identifying faces. The dimensionality reduction associated with this method would allow a recognition module to work with a vector considerably smaller than the original image size. This would considerably reduce the complexity of the recognition process. After training multiple networks configurations on numerous images sets, no network was found that adequately performed such a PCA combining of faces.   However, there where some networks that showed some indications of being able to perform such a combining. These networks where not, however, able to recreate faces reliably enough to use as the bases of a recognition module. Further study in this area should begin by using richer training sets in an attempt to force the network to learn multiple individuals.

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APPENDIX A – TERMS

Facial Image Features [Yang 2004]

Pose (Out-of-Plane Rotation): frontal, 45 degree, profile, upside down.

Structural components: beards, mustaches, and glasses.

Facial expression: face appearance is directly affected by a person's facial expression.

Occlusion: faces may be partially occluded by other objects.

Orientation (In-Plane Rotation): face appearance directly vary for different rotations about the camera's optical axis.

Imaging conditions: lighting (spectra, source distribution and intensity) and camera characteristics (sensor response, gain control, lenses), and resolution.

Face Detection Algorithm Categories [Yang 2002]

Knowledge-based methods: These rule-based methods encode human knowledge of what constitutes a typical face. Usually, the rules capture the relationships between facial features. These methods are designed mainly for face localization.

Feature invariant approaches: These algorithms aim to find structural features that exist even when the pose, viewpoint, or lighting conditions vary, and then use the these to locate faces. These methods are designed mainly for face localization.

Template matching methods: Several standard patterns of a face are stored to describe the face as a whole or the facial features separately. The correlations between an input image and the stored patterns are computed for detection. These methods have been used for both face localization and detection.

Appearance-based methods: In contrast to template matching, the models (or templates) are learned from a set of training images which should capture the representative variability of facial appearance. These learned models are then used for detection. These methods are designed mainly for face detection.

APPENDIX B – CORRECTNESS OF NEURAL NETWORK CODE

The correctness of the neural network code was tested using both black box and white box testing methods. In addition, all subroutines and member functions where tested individually prior to being included in the complete algorithm. After verification of the implementation of the algorithms, numerous feasibility test where performed to verify the use of the neural network in a PCA configuration.

White Box Testing

White box testing focused mainly on the neural network computations. Since these computations are extensive, it was felt necessary to perform the computations by hand and verify the correctness of the algorithm. In order to accomplish this, a few very small networks where given inputs, target outputs, and set weights. Both the feed forward computations and the back propagation of errors computations where performed by hand and compared to the network. The various values associated with each node in the network where compared with those computed by hand. It was determined that the network computations where correct.

Black Box Testing

Black box testing consisted of training the neural network on numerous test cases to verify its ability to learn. The objective of this testing was to verify the functionality of the entire neural network class (NeuralNet) and its associated classes. These test where designed specifically to demonstrate errors that could not easily be demonstrated by hand calculations. These test where also used to verify the member functions such as input, output, scaling, saving, loading, and initialization functions that are not directly related to the numeric computations.

Black Box Testing Examples

A few of the numerous test cases used to verify the neural network code are presented here. The first case is a simple sinusoidal function. The input and output where scaled and converted to single byte char values. This test verifies the NeuralNet classes i/o routines when presented with single byte char data. As can be seen in Figure B.1 the small 1-3-1 network does a reasonable job of learning the sine function. A larger network (1-5-1) is trained on a more complex sinusoidal function in Figure B.2. This test demonstrates the networks ability to learn.

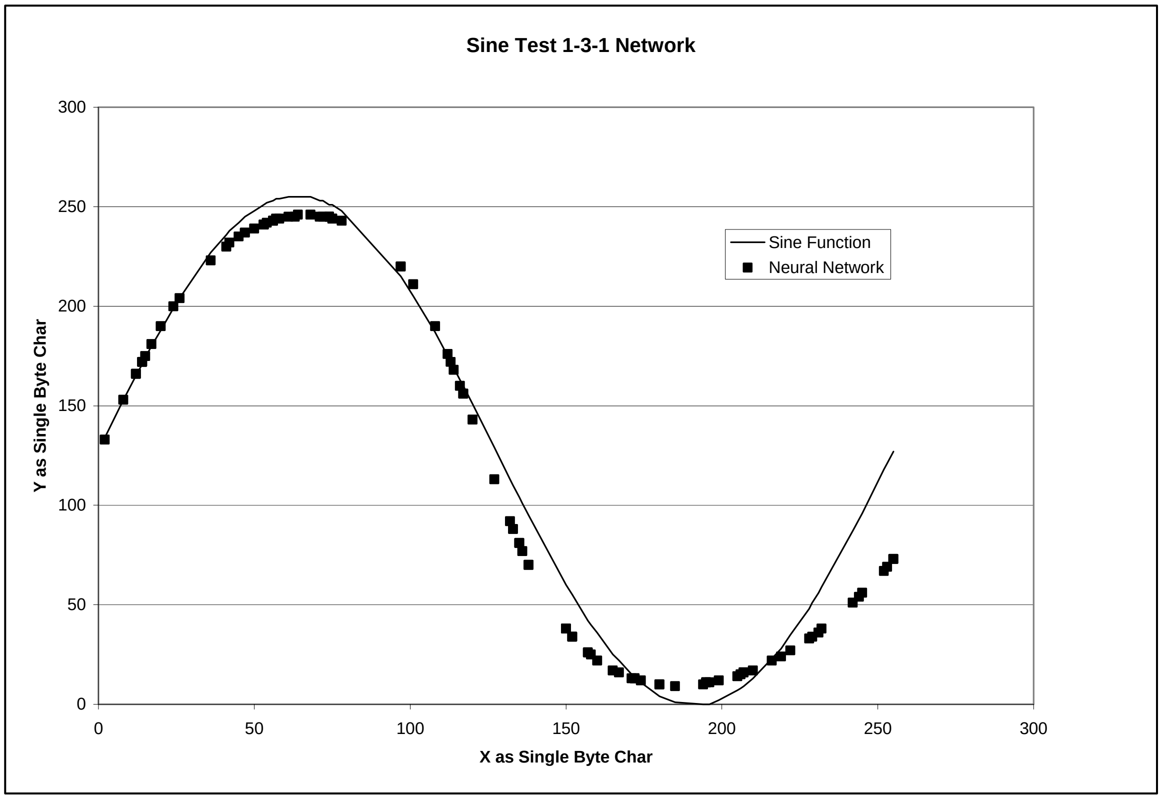

Figure B.1 NeuralNet Test - Sine

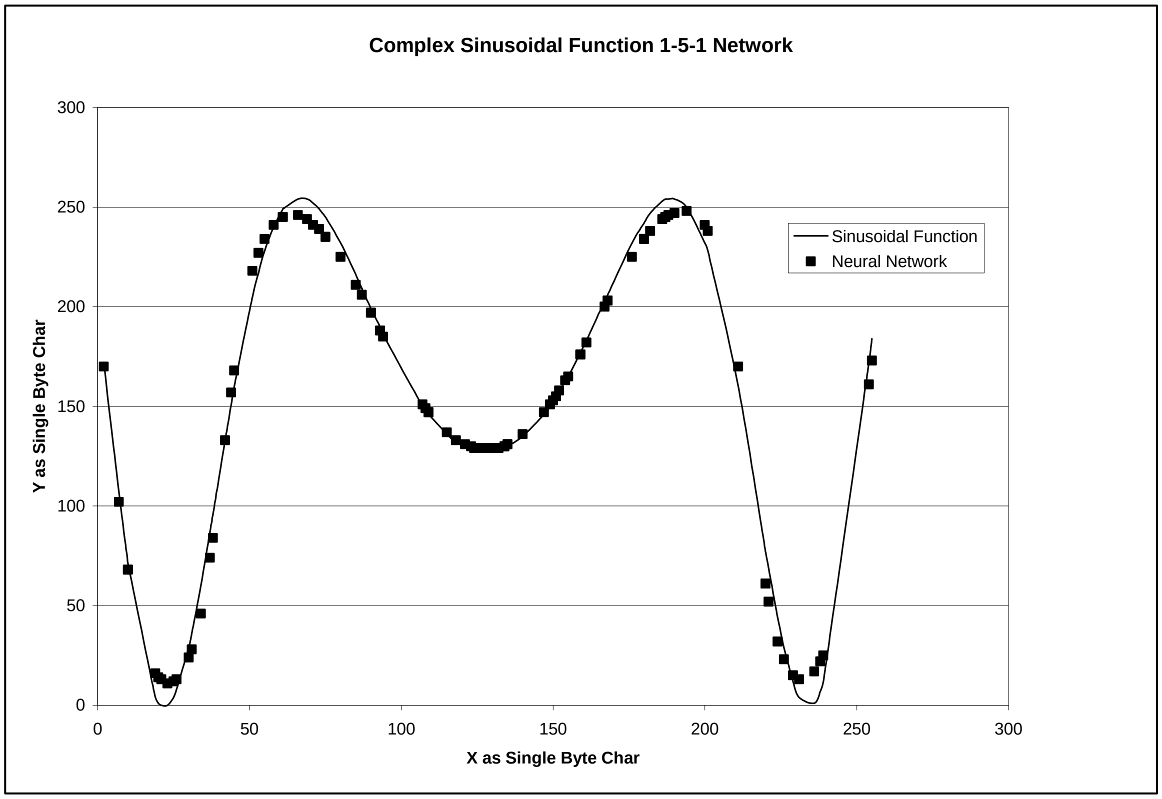

Figure B.2 NeuralNet Test – Complex Sinusoidal Function

PCA Configuration Verification

The next set of test performed sought to verify the use of the neural network in a configuration like that used for PCA. Namely, the inputs and the target outputs are the same and the network is structured with a bottleneck layer. A bottleneck layer is a hidden layer with fewer nodes that the number of inputs. For the network to be successfully used to perform a PCA like dimensional reduction, the network must successfully reproduce the inputs at the outputs. Some of the testing examples used are described below.

The first PCA test involved two simple linear functions, $y_0 = x$ and $y_1 = -x$. Random x values between -1 and 1 where used to calculate these two inputs. A 2-1-2 network was trained to reproduce the input at the output. Figure B.3 shows the results of this test. This case is somewhat trivial because one of the inputs is the principle component the network is expected to utilize.

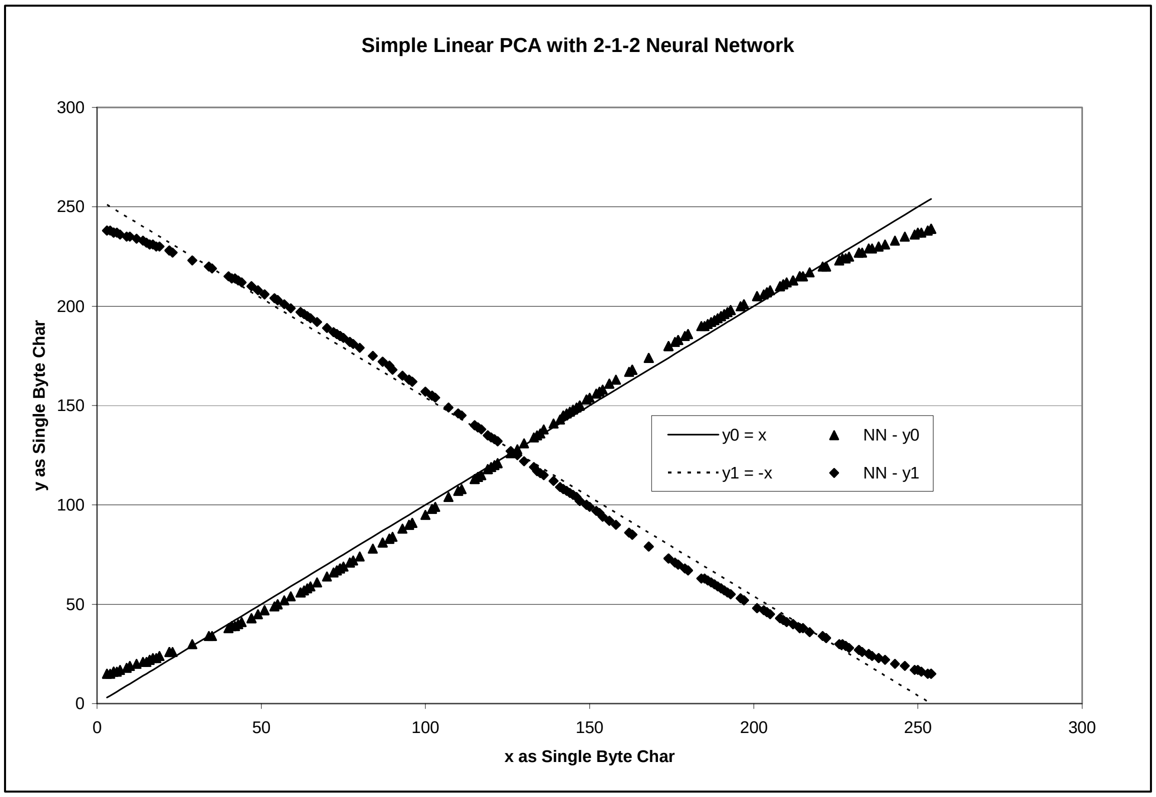

Figure B.3 PCA Test with Simple Linear Functions

The second PCA test was designed such that the principle component the functions where based on was not included in the input set. In this test y_0 = x*x and y_1 = 1.5*x*x – x + 0.5. Again, this test is very similar to the first test, however, the principle component x is not passed as an input to the network. The smallest network found to be capable of learning this mapping was a 2-2-1-2-2 network. Figure B.4 shows the output of this network.

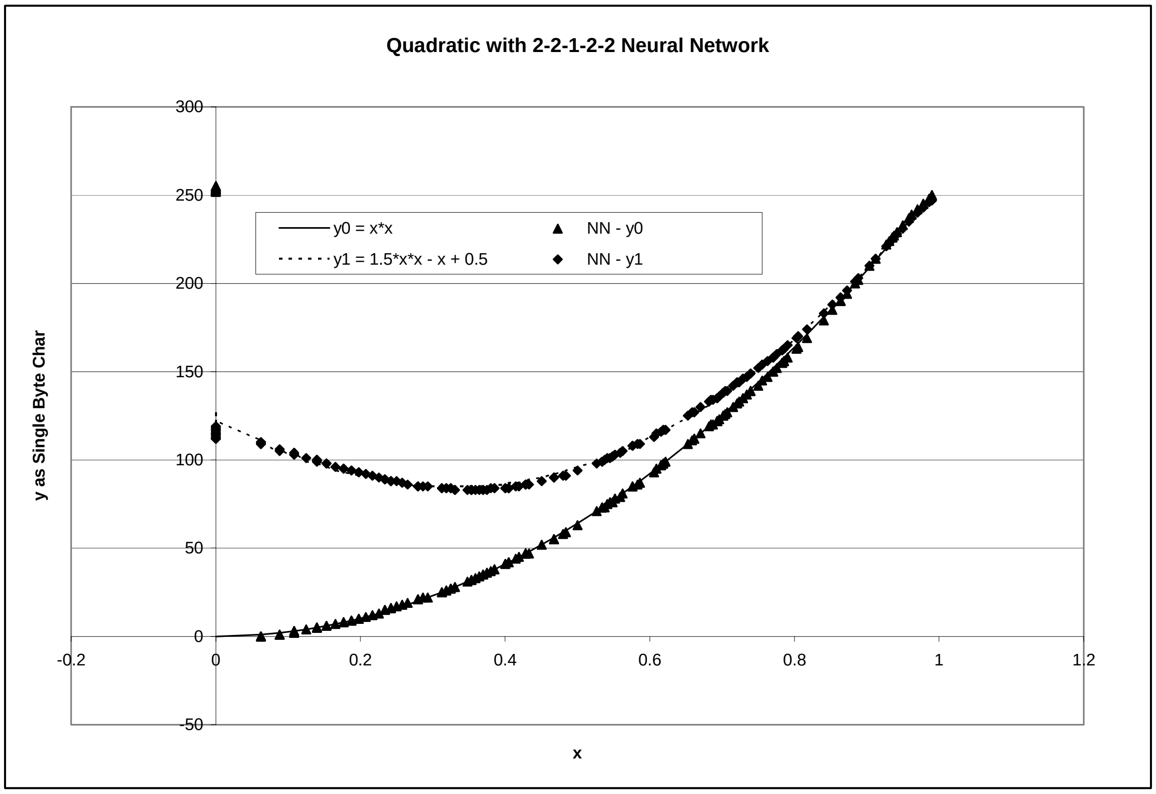

Figure B.4 PCA Test with Quadratic Functions