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ECE 479: Intelligent Robotics II

Human Facial Emotion Recognition Using OpenCV and Microsoft Kinect

Final Project Report

Table of Contents

1 INTRODUCTION 4

2 BACKGROUND 4

2.1 OPENCV 4
2.2 UNIVERSALITY OF HUMAN EMOTIONS 4
2.3 EMOTION RECOGNITION SYSTEM (ERS) 4
2.3.1 Principle Component Analysis (PCA) 5
2.3.2 Artificial Neural Networks (ANN) 5

3 FUNDAMENTALS AND IMPLEMENTATION OF PCA IN OPENCV 5

3.1 CALCULATING COVARIANCE MATRIX 7
3.2 FINDING EIGENVALUES AND EIGENVECTORS 7
3.3 THE MEANING OF EIGENVALUES AND EIGENVECTORS 9

4 PCA IN IMAGE COMPRESSION AND FEATURE EXTRACTION 13

4.1 APPLYING PCA TO A SET OF FACE IMAGES 13
4.2 IMPLEMENTATION OF PCA IN OPENCV 16
4.2.1 Introduction to Facial Expression Database 16
4.2.2 Apply PCA to the Facial Expression Database 17

5 NEURAL NETWORK TRAINING 20

6 KINECT INTERFACE 23

7 FUTURE EXPANSIONS OF PROJECT 27

8 PROJECT CONCLUSIONS 27

APPENDIX A INSTALLING OPENCV AND OPENKINECT 28

APPENDIX B PCA AND NN SOURCE CODE 29

CFACERECOGNIZER.H 29
NEUNET.H 29
CFACERECOGNIZER.CPP 30
EMOREGBYANN.CPP 32

APPENDIX C KINECT INTERFACE SOURCE CODE 38

MAKEFILE 38
KINECT.H 39
KINECTAPI.H 41
KINECT.CPP 42
KINECTAPI.CPP 44

APPENDIX D WORKS CITED 47

APPENDIX E RELATED REFERENCES 47

List of Tables, Figures, and Equations

TABLE 1: A 2-DIMENSIONAL DATASET USED FOR DESCRIBING PCA 6
EQUATION 1: FORMULA TO COMPUTE COVARIANCE MATRIX 7
TABLE 2: ALL COVARIANCE PARAMETERS OF 2-VARIABLE COVARIANCE MATRIX 7
EQUATION 2: DEFINITION OF EIGENVECTORS AND EIGENVALUES 7
EQUATION 3: CHARACTERISTIC POLYNOMIAL OF A SQUARE MATRIX A 8
TABLE 3: DATA VARIANCE FROM AVERAGE VALUES OF X AND Y 10
FIGURE 1: DATA VARIANCE FROM AVERAGE VALUES 11
FIGURE 2: TWO EIGENVECTORS OF THE GIVEN DATASET 12
FIGURE 3: SOME EXAMPLES OF EIGENFACES 14
FIGURE 4: COMPUTE DATA MATRIX OF A DATABASE HAVING M IMAGES 15
EQUATION 4: AVERAGE FACE FORMULA 15
EQUATION 5: SUBTRACTING IMAGE VECTORS BY AVERAGE VECTOR 15
EQUATION 6: COVARIANCE MATRIX C 15
EQUATION 7: FORMULA FOR IDENTIFYING EIGENFACES 16
EQUATION 8: FORMULA FOR PROJECTING NEW IMAGE TO FACE-SPACE 16
FIGURE 5: IMAGES FROM FACIAL EXPRESSION DATABASE 17
FIGURE 6: IMAGES FROM FACIAL EXPRESSION DATABASE 17
FIGURE 7: THE AVERAGE FACE COMPUTED FROM THE FACE MATRIX 18
FIGURE 8: THE FIRST SIX EIGENFACES COMPUTED FROM THE FACE MATRIX 19
FIGURE 9: A SET OF WEIGHT OBTAINED FROM PROJECTING AN IMAGE TO THE FACE-SPACE 20
FIGURE 10: EXAMPLE ACTIVATION FUNCTION BASED ON SIGMOID 21
FIGURE 11: BASIC ARCHITECTURE OF PCA CONNECTED TO BACK PROPAGATION NEURAL NETWORK 22
EQUATION 9: CHAIN RULE EXPANSION TO DERIVE LEARNING RULE 23
EQUATION 10: DELTA LEARNING RULE 23
TABLE 4: PERFORMANCE COMPARISON BETWEEN DIFFERENT CHOICES OF HIDDEN LAYERS AND THE NUMBER OF NEURONS IN THE HIDDEN LAYERS. 23
FIGURE 12: ARCHITECTURE OF KINECT INTERFACE, AND SUGGESTION FOR FUTURE EXPANSION. 25
TABLE 5: GENERALIZED OPENCV KINECT API 26

1 Introduction

The aim of this project is to use OpenCV and C++ to implement a facial expression recognition system that can be used in robotic applications. In a humanoid robot, the interaction between robot and people is critical. Therefore, integrating an emotion recognition system (ERS) into this kind of robot will make the interaction between robots and people more interesting and engaging.

An important point of implementing ERS in robots is real time processing of images taken from robots' camera. Therefore, a fast processing algorithm would be more desirable in this project.

This project is implemented using OpenCV and C++ programming language. OpenCV is an open library for computer vision. More discussion about OpenCV and the reason of using it will be discussed in section 2 (Background).

2 Background

2.1 OpenCV

OpenCV is an Open Source Computer Vision library. It includes programming functions and more than 2500 optimized algorithms for real time computer vision. OpenCV has a large support community which is a great advantage for software development. At the moment of writing this report, OpenCV has C, C++ and Python interfaces and is available on Windows, Linux, Android and Mac.

Its main focus on real time processing (and portability) makes OpenCV an ideal choice for ERS instead of implementations done in programming languages such as MATLAB.

2.2 Universality of Human Emotions

Before going into details on understanding Emotion Recognition System, it is important to know some basic facts about human emotions. Generally, there are 7 universal human emotions: anger, disgust, happiness, sadness, fear, surprise and neutral. Dr. Paul Ekman [3] mentions in his research that different cultures show the same facial expressions when experiencing the same emotion unless culture-specific display rules interfere.

These 7 human emotions are recognized by Action Units which are groups of facial muscles that when activated together result in a particular movement of facial features. For example, an eyebrow being raised and a mouth being opened can describe a "surprised" emotion.

2.3 Emotion Recognition System (ERS)

The emotion recognition system has been a significant field in human-computer interaction. It is a considerably challenging field to generate an intelligent computer that is able to identify and understand human emotions for various vital purposes, e.g. security, society, or entertainment. Many research studies have been carried out in order to produce an accurate and effective emotion recognition system. Emotion recognition methods can be classified into different categories along a number of dimensions: speech emotion recognition vs. facial emotion recognition; machine learning method vs. statistical method. Facial expression method can also be classified based on input data consisting of a sequence video or static images. This project will focus on recognizing emotions based on facial expression. The main purpose of this project is to be applied in robotic application. Therefore, the ability to analyze live video from a robot's camera and distinguish different emotions is necessary. The accuracy is not a critical purpose when weighed against other system performance, particularly speed. (Real time, efficient, processing is much more important than 100% accuracy.)

The method used in this project for ERS is to combine Principle Component Analysis (PCA) with a Machine Learning algorithm - Artificial Neural Network (ANN).

ERS is separated into 2 phases: training phase and testing phase. In training phase, PCA is used for image compression and feature extraction. First, we need to apply PCA to a set of training images. The output of this PCA will be a set of feature weights (more detail is discussed in the section below). These sets of weights are the input of a Back Propagation Neural Network, which performs the task of machine learning. It will determine which specific features (and combinations of these features) best describe which specific emotions. In the testing phase, PCA is used to project a new image to a space defined by PCA for image compression. In this way, the PCA and ANN work together to develop a set of combined weights that can be used with real time video data.

2.3.1 Principle Component Analysis (PCA)

PCA was invented in 1901 by Karl Pearson [2]. It is a statistical approach which compresses multi-variable data by identifying variance in the dataset and representing the data in terms of this variance. This is achieved by building a covariance matrix and finding the eigenvectors and eigenvalues of the covariance matrix. The covariance matrix identifies the variance of the dataset. The eigenvector with the largest corresponding eigenvalue identifies the greatest variance in the dataset. Each eigenvector contributes to identifying variance in the dataset and is referred to as the principle component. This process allowed the interpretation of complex dataset and became a popular tool in many fields of research. In image processing, PCA is well-known for feature extraction and data compression.

Because of its ability for data compression, PCA significantly reduces computational requirements of the overall system. Therefore, it is an ideal choice to be integrated into real-time robotic applications; it reduces the original data to a minimal dataset that is still representative of the original data.

2.3.2 Artificial Neural Networks (ANN)

Artificial Neural Network is a machine learning algorithm that is based on biological neural networks (the biological brain). An ANN consists of interconnected groups of artificial neurons that can be represented in either hardware or software. ANN is an adaptive system that changes its structure based on external information that flows through the network during the learning phase. In image processing, neural network is used to obtain complex relationships between inputs and outputs to find particular pattern in data. In our context, we will be using the eigenvectors/eigenvalues produced during the PCA phase as inputs to the neural network, and the 7 emotions we are identifying will correspond to the outputs of the neural network.

3 Fundamentals and Implementation of PCA in OpenCV

The aim of this section is to explain the use of PCA in image compression by using a simple example. We will go through all necessary steps to calculate principle components of a given dataset. The next section will use a specific example in image processing to help readers have a better understanding about PCA.

Let’s consider a 2-dimensional dataset as shown in the following table:

X	Y
1	38
3	33
6	30
10	35
9	38
12	32
20	48
22	47
19	45
16	50
25	53
26	52
18	55
16	58
33	62
30	65
29	67
27	62
20	68
31	70
$\overline{X} = 18.65$	$\overline{Y} = 50.4$

Table 1: A 2-dimensional dataset used for describing PCA

The preceding dataset is constructed in such a way that 2 variables have positive correlation. Positive correlation means Y increases in respect to X generally.
Next step, the covariance matrix will be calculated from the table above.

3.1 Calculating covariance matrix

To find covariance matrix of a given dataset, the following formula is used to compute covariance parameters in the matrix:

$$COV(X,Y) = \frac{1}{N-1} \sum_{i-1}^{N} (X_i - \overline{X})(Y_i - \overline{Y})$$

Equation 1: Formula to compute covariance matrix

A covariance matrix for 2-variable dataset will have following form:

$$\begin{bmatrix} \mathrm{cov}(x, x) & \mathrm{cov}(x, y) \\ \mathrm{cov}(y, x) & \mathrm{cov}(y, y) \end{bmatrix}$$

Based on Equation 1, we can calculate all covariance parameters of the matrix as shown below:

cov(X,X)	cov(X,Y)	cov(Y,X)	cov(Y,Y)
90.34	104.25	104.25	167.83

Table 2: All covariance parameters of 2-variable covariance matrix

One can see that covariance values of cov(X,Y) and cov(Y,X) are both positive. This fact shows the positive correlation between X and Y as assumed from the beginning. If these two values are negative, it shows that they have negative correlation which means one will increase value when the other one decreases. One other case is when these two values are both zero, there's no correlation between these two variables.

From this example, it is apparent that the correlation between variables in a dataset can be obtained by examining covariance matrix. This result is significant with a dataset having a large number of variables. Applying this analysis for such system can show which variables have the most effect in a system.

The next step to find principle components of the given dataset is to compute eigenvalues and eigenvectors from the covariance matrix.

3.2 Finding eigenvalues and eigenvectors

Eigenvectors of a square matrix are the non-zero vectors that remain parallel to the matrix after being multiplied by the matrix [4]. This definition can be briefly described by the following expression:

$$Av = \lambda v$$

Equation 2: Definition of eigenvectors and eigenvalues

In the equation: A is a square matrix, λ is eigenvalue and v is eigenvector.
Eigenvalues and eigenvectors can be found by solving characteristic polynomial of the square matrix A:

$$det(A - \lambda I) = 0$$

Equation 3: Characteristic polynomial of a square matrix A

In this particular example that we are considering, square matrix A is the covariance matrix, and its characteristic polynomial is shown below:

$$\det\left(\begin{bmatrix} 90.34-\lambda & 104.25 \\ 104.25 & 167.83-\lambda \end{bmatrix}\right)$$

$$= (90.34-\lambda)(167.83-\lambda) - (104.25)(104.25)$$
$$= (90.34-\lambda)(167.83-\lambda) - 10868.1$$
$$= \lambda^2 - 258.17\lambda + 4293.66$$

$$\lambda_1 = 17.869$$
$$\lambda_2 = 240.31$$

Solve characteristic polynomial, we obtain 2 eigenvalues. It is possible, now, to find eigenvectors of the covariance matrix.

In this example, square matrix A has the following form:

$$A = \begin{bmatrix} a & b \\ c & d \end{bmatrix}$$

Eigenvectors for this matrix can be defined as:

$$v_1 = \begin{vmatrix} \lambda_1 - d \\ c \end{vmatrix}$$

$$v_2 = \begin{vmatrix} \lambda_2 - d \\ c \end{vmatrix}$$

With $\lambda_1 = 17.869$, eigenvector v_1 is found as:

$$V_1 = \begin{bmatrix} 17.869 \ -167.83 \\ 104.25 \end{bmatrix}$$

$$V_1 = \begin{bmatrix} -149.961 \\ 104.25 \end{bmatrix}$$

This eigenvector can be normalized by the following method:

$$d = \sqrt{a^2 + b^2}$$
$$d = \sqrt{-149.961^2 + 104.25^2} = 182.637$$

$$\begin{bmatrix} \dfrac{-149.961}{d} \\ \dfrac{104.25}{d} \end{bmatrix} = \begin{bmatrix} -0.82108 \\ 0.57080 \end{bmatrix}$$

Therefore, normalized eigenvector v_1 is:

$$v_1 = \begin{bmatrix} -0.82108 \\ 0.57080 \end{bmatrix}$$

Similarly, normalized eigenvector v_2 is:

$$v_2 = \begin{bmatrix} 0.5708 \\ 0.8210 \end{bmatrix}$$

To summarize, the given dataset has 2 eigenvalues and 2 equivalent eigenvectors as following:
$\lambda_1 = 17.869$:

$$v_1 = \begin{bmatrix} -0.82108 \\ 0.57080 \end{bmatrix}$$

$\lambda_2 = 240.31$:

$$v_2 = \begin{bmatrix} 0.5708 \\ 0.8210 \end{bmatrix}$$

Eigenvalues and eigenvectors obtained from the covariance matrix will be used to identify data patterns in the original dataset.

3.3 The meaning of eigenvalues and eigenvectors

In this section, we will discuss the practical meaning of eigenvalues and eigenvectors. First of all, we will plot a diagram showing data variance of the given dataset from average values.

X - $\overline{X}$	Y - $\overline{Y}$

-17.65	-12.4
-15.65	-17.4
-12.65	-20.4
-8.65	-15.4
-9.65	-12.4
-6.65	-18.4
1.35	-2.4
3.35	-3.4
0.35	-5.4
-2.65	-0.4
6.35	2.6
7.35	1.6
-0.65	4.6
-2.65	7.6
14.35	11.6
11.35	14.6
10.35	16.6
8.35	11.6
1.35	17.6
12.35	19.6

Table 3: Data variance from average values of X and Y

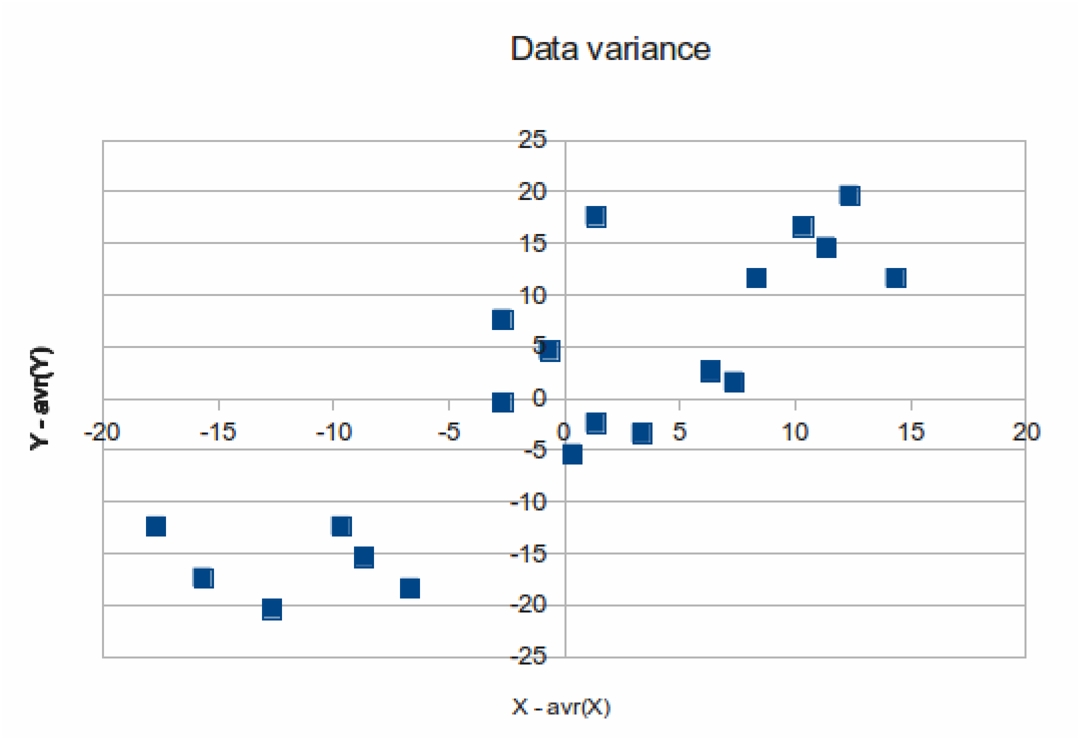


Figure 1: Data variance from average values

The eigenvectors of that dataset then will show the major trend of the variance in the following plot.

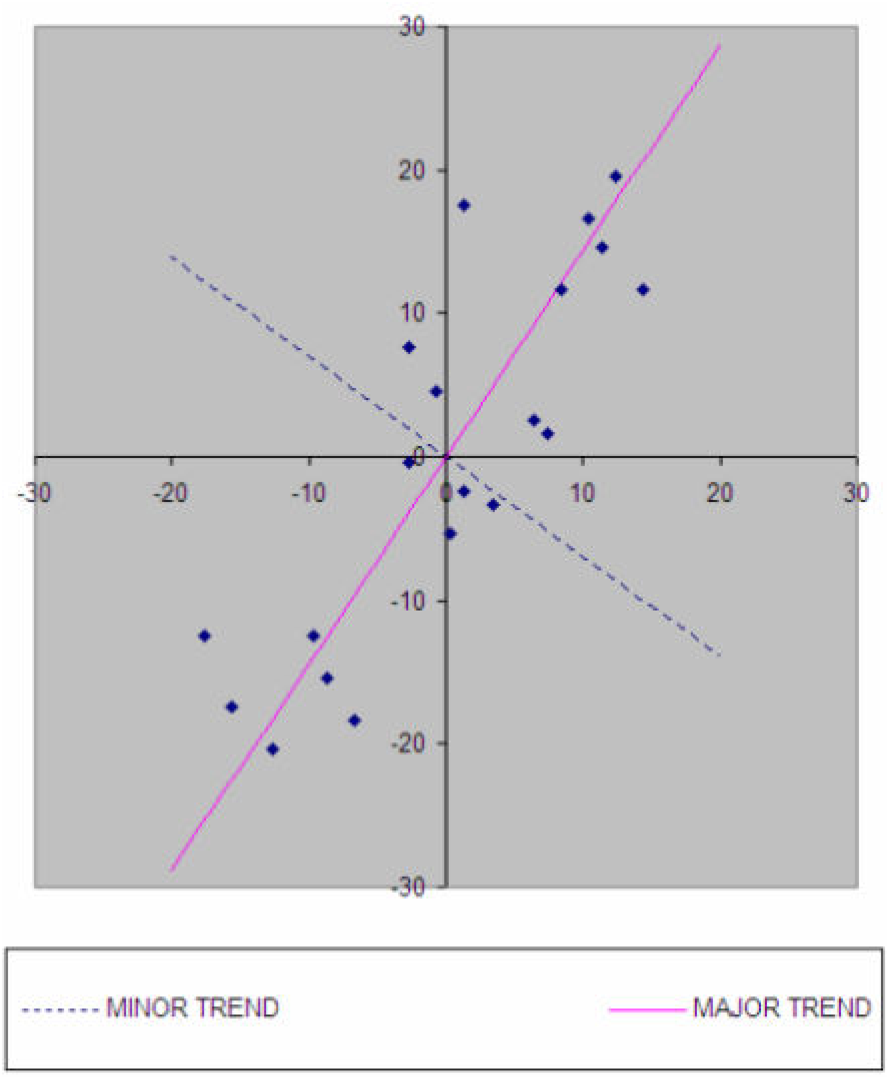


Figure 2: Two eigenvectors of the given dataset

From the plot, we can see that the eigenvector with larger eigenvalue (λ_2 *and* v_2 in this case) express the major trend of data variance. And the second eigenvector shows the minor trend of data variance from the average values of X and Y. These two eigenvectors are perpendicular.

Each eigenvector is called principle component of a dataset. Eigenvector with largest equivalent eigenvalue is called main principle component. With a given dataset, eigenvalues need to be sorted from largest to smallest values. Eigenvectors then will be sorted in respect to theirs corresponding eigenvalues. Principle component is perpendicular to each other. All principle components of a dataset form an orthogonal space in which each principle component is a coordinate.

With this example, two principle components help in identifying pattern in the dataset (how much data vary from the mean and in which direction). Each principle component represents a certain portion of the entire data. The number of principle components depends on the size of covariance matrix. In this example, the covariance matrix is 2x2. Therefore, the maximum number of principle components is 2.

4 PCA in Image Compression and Feature Extraction

In image processing, a dataset contains a lot of images. Each image is considered as a ‘point’ in a dataset. By applying PCA to that dataset, we can extract the features described by the dataset. By projecting an image, which doesn’t belong to the given dataset, to an orthogonal space formed by PCA, that image can be described as a point in the orthogonal space. And its coordinates in the space express how much the image contains the features described by the given dataset.

With a dataset with N images, the maximum number of principle components is N. Projecting an image to the orthogonal space formed by PCA also results in decreasing data needed to describe the image. For example, giving a dataset with 100 images, the maximum number of principle components is 100. Therefore, the number of coordinates in orthogonal space is also 100. A 150x150 image contains 22500 pixels. In the orthogonal space given by the dataset, that image only needs 100 coordinates to be described correctly. Thus, PCA can be used for image compression. The following section will discuss more detail how to apply PCA to a set of face images.

4.1 Applying PCA to a Set of Face Images

One image can be converted into a vector by concatenating either the rows or the columns of the image together. Applying this principle to all images in the set to create a matrix with each image described by a row or column. This matrix then can be used to compute the covariance matrix, eigenvectors (principle components) and eigenvalues of the set of images. The eigenvectors are sorted by their corresponding eigenvalues. These principle components describe the patterns in the dataset.

In the particular case of face images, all principle components form a space of faces (or face-space). Each principle component contributes a certain amount of feature to represent the face-space. In this situation, eigenvector is also called eigenface. These eigenfaces are called “standardized face ingredients” [5]. With a large enough face database, any human face can be considered as a combination of these standard faces by projecting that human face to face-space. For example, one’s face can be composed of the average face plus 5% of eigenface 1, 20% of eigenface 2 and 60% of eigenface 3...

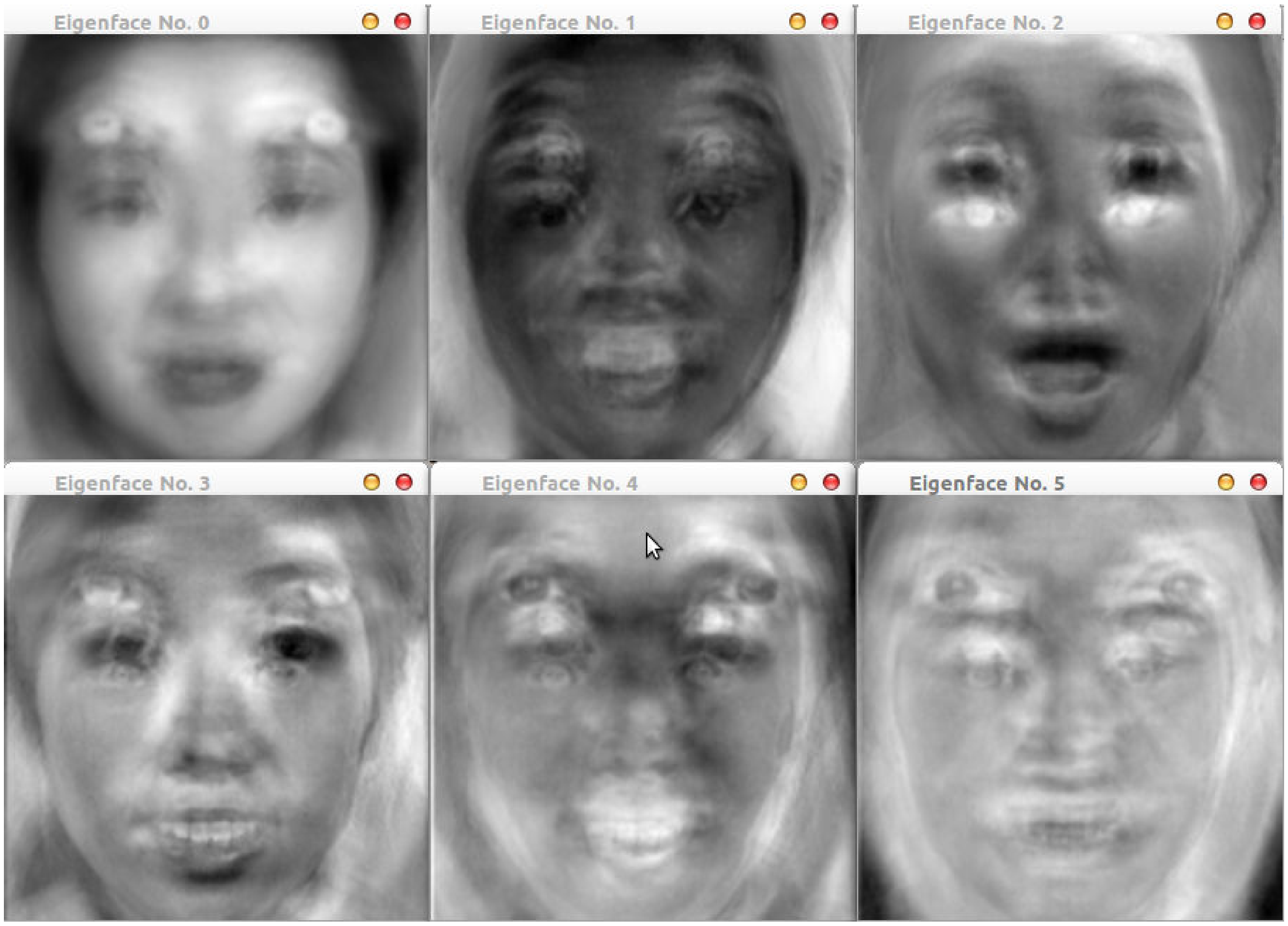


Figure 3: Some examples of eigenfaces

The following steps describe how to apply PCA to a set of face images theoretically. A specific example will be given in the next section.

- *Step 1 - Obtaining Grayscale image dataset:* this step is not quite necessary because many of available databases are grayscale. Also in this step, all images need to be converted to a same size.
- *Step 2 - Converting images into vectors:* each image is converted to a column vector in the dataset matrix Γ. For example, a Γ_i vector is obtained by resizing each NxN image into a N^2x1 vector. If there are M images in the database, the database matrix has dimension of N^2xM.

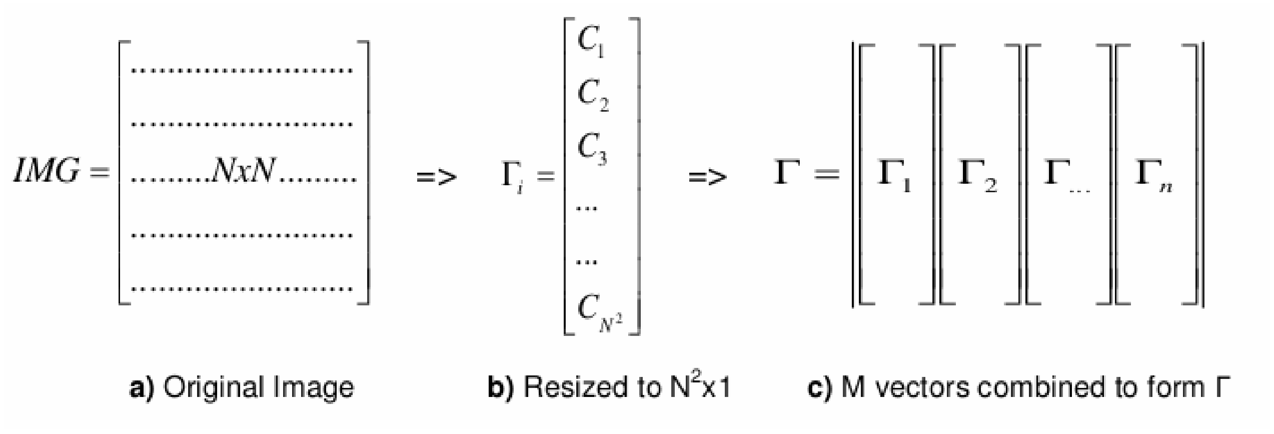


Figure 4: Compute data matrix of a database having M images

- *Step 3 - Compute Average Face:* because each face is expressed as a vector in data matrix, average face is also known as average vector. Average vector is computed by the following formula:

$$\Psi = \frac{1}{M} \sum_{i=1}^{M} \Gamma_i$$

Equation 4: Average face formula

  Faces are generally similar and share many common features. By computing average face and subtracting it from the faces in the database, we can remove the common feature shared by all the faces. Using only the differences of each face results in a better distribution of the face data, and also allows better feature extraction from the face database.
- *Step 4 - Subtract Average Vector from all vectors:* to remove the common feature shared by all face images, the original Γ matrix is modified by subtracting individual column vectors (images) by the average vector (average face).

$$\Phi_i = \Gamma_i - \Psi$$

Equation 5: Subtracting image vectors by average vector

  Φ_i is called mean-centered image.
- *Step 5 - Generating the Covariance Matrix:* the matrix Φ is used to generate the covariance matrix. The covariance matrix is found by the similar method used in the example in section 3.1. The corresponding formula is given as following:

$$C = \frac{1}{M} \sum_{n=1}^{M} \Phi_n \Phi_n^T$$

Equation 6: Covariance matrix C

- *Step 6 - Compute Eigenvectors and Eigenvalues:* eigenvectors and eigenvalues are computed from the covariance matrix C. Detail calculation method is not listed here because the main purpose of this paper is not about mathematics calculation. More references about practical method to compute eigenvalues and eigenvectors are listed in Appendix.

- *Step 7 - Identifying Principle Components:* computed eigenvalues are sorted from largest to smallest values. Therefore, the corresponding eigenvectors are also sorted in respect to theirs eigenvalues. These eigenvectors are principle components of the given face database. Each principle component is perpendicular to each other, and together form an orthogonal coordinate system.
- *Step 8 - Calculating Eigenfaces:* after eigenvectors have been sorted, they are multiplied by the mean-centered images Φ_i to generate eigenfaces. Therefore, each eigenvector represents an eigenface which identifies a particular feature in the face-space. The following equation is used to compute eigenfaces:

$$\mu_i = \sum_{k=1}^{M} V_{ik}\Phi_k \quad \text{For i = 1, 2, . . ., M}$$

Equation 7: Formula for Identifying eigenfaces

In above equation, V_{ik} is principle components (eigenvectors) of the covariance matrix identified by the given dataset.
The process of finding eigenfaces is also called feature extraction because eigenfaces identify particular features described by the given face images.

- *Step 9 - Projecting an image to face-space or Image Compression:* each new image can be converted into a set of weights (or coordinates in the orthogonal face-space) by being projected onto the eigenfaces. This is obtained by applying the following equation:

$$\omega_k = \mu_k^T(\Gamma_{new} - \Psi) \quad \text{For k = 1 to M}$$

Equation 8: Formula for projecting new image to face-space

ω_k with k = 1..M is the set of weights (or coordinates in the face-space) used to identify the new image in the face-space. Generally, M is much smaller than the image size. Therefore, the new image is compressed significantly by projecting it to the face-space. The set of weights obtained from the projection also describes the features contained in the given image. For example, an image can be a combination of the average face plus 5% of eigenface 1, 20% of eigenface 2 and 60% of eigenface 3...

4.2 Implementation of PCA in OpenCV

In this section, a specific example will be given to illustrate the actual implementation of PCA by OpenCV library.

4.2.1 Introduction to Facial Expression Database

One of the key factor to a successful ERS is a good and large enough facial expression database. This is also an obstacle in this project because there are not so many available facial databases. Some good databases as MMI face database and Cohn-Kanade Facial Expression Database are available for research use but taking a great amount of time for their system to grant access for students. Therefore, these databases are not included in this paper. However, the result of this paper can be improved using databases from these sources when they are available.

In this paper, we use JAFFE database (The Japanese Female Facial Expression Database) and another database obtained from a paper about facial expression research [1]. Some of the images from these 2 databases are shown below.

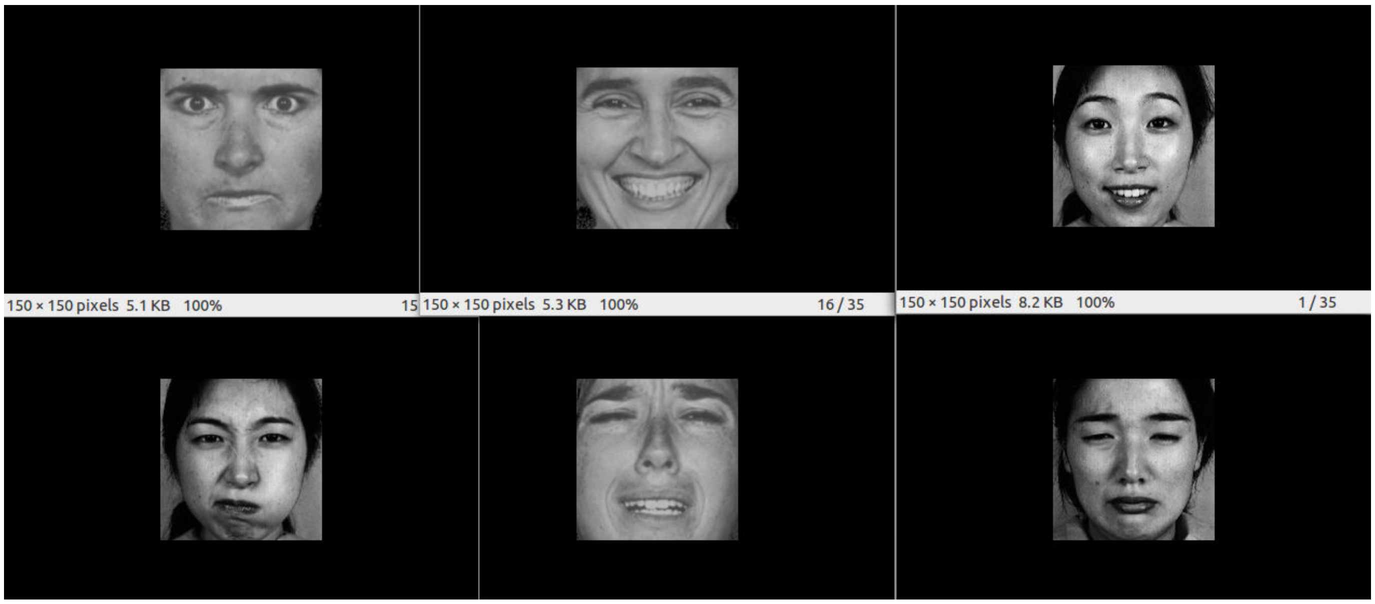

150 × 150 pixels 5.1 KB 100%
15
150 × 150 pixels 5.3 KB 100%
16 / 35
150 × 150 pixels 8.2 KB 100%
1 / 35

Figure 5: Images from facial expression database

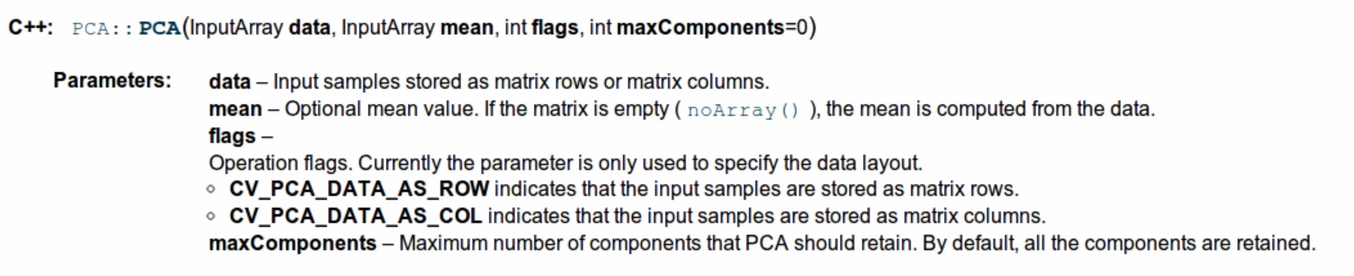
The number of images in the database is 97. All images are grayscale and converted to the same size 150x150.

These images are classified to 7 categories corresponding to 7 emotions: happy, sad, disgust, angry, surprise, fear and neutral.

4.2.2 Apply PCA to the Facial Expression Database

According to the steps mentioned in section 4.1, after obtaining grayscale images which are already available in the database, all images are concatenated to form a matrix whose columns are images in the database.

OpenCV library has PCA class that is designed specifically for PCA application.



C++: `PCA::PCA`(InputArray **data**, InputArray **mean**, int **flags**, int **maxComponents**=0)

Parameters:
data – Input samples stored as matrix rows or matrix columns.
mean – Optional mean value. If the matrix is empty (`noArray()`), the mean is computed from the data.
flags –
Operation flags. Currently the parameter is only used to specify the data layout.
- **CV_PCA_DATA_AS_ROW** indicates that the input samples are stored as matrix rows.
- **CV_PCA_DATA_AS_COL** indicates that the input samples are stored as matrix columns.

maxComponents – Maximum number of components that PCA should retain. By default, all the components are retained.

Figure 6: Images from facial expression database

We apply this class to the matrix constructed by all the face images in the database. In this matrix, images are converted to one column. Therefore, CV_PCA_DATA_AS_COL is chosen as flag.

After applying this class to the matrix, it automatically computes the average vector, subtracts all image vectors by this average vector, and compute eigenvectors and eigenvalues from the mean-centered matrix. The following pictures are average face and some eigenfaces computed by using PCA class in the matrix.

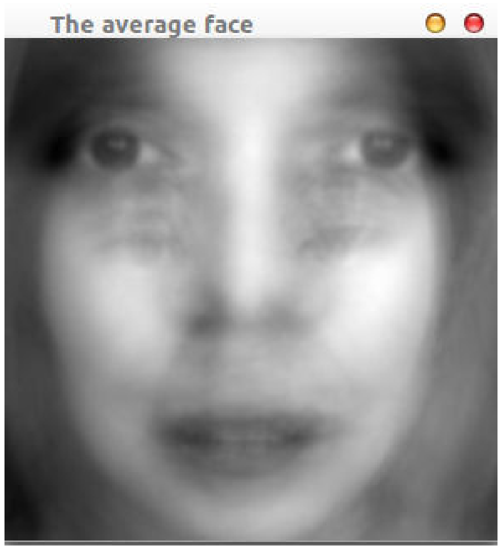


Figure 7: The average face computed from the face matrix

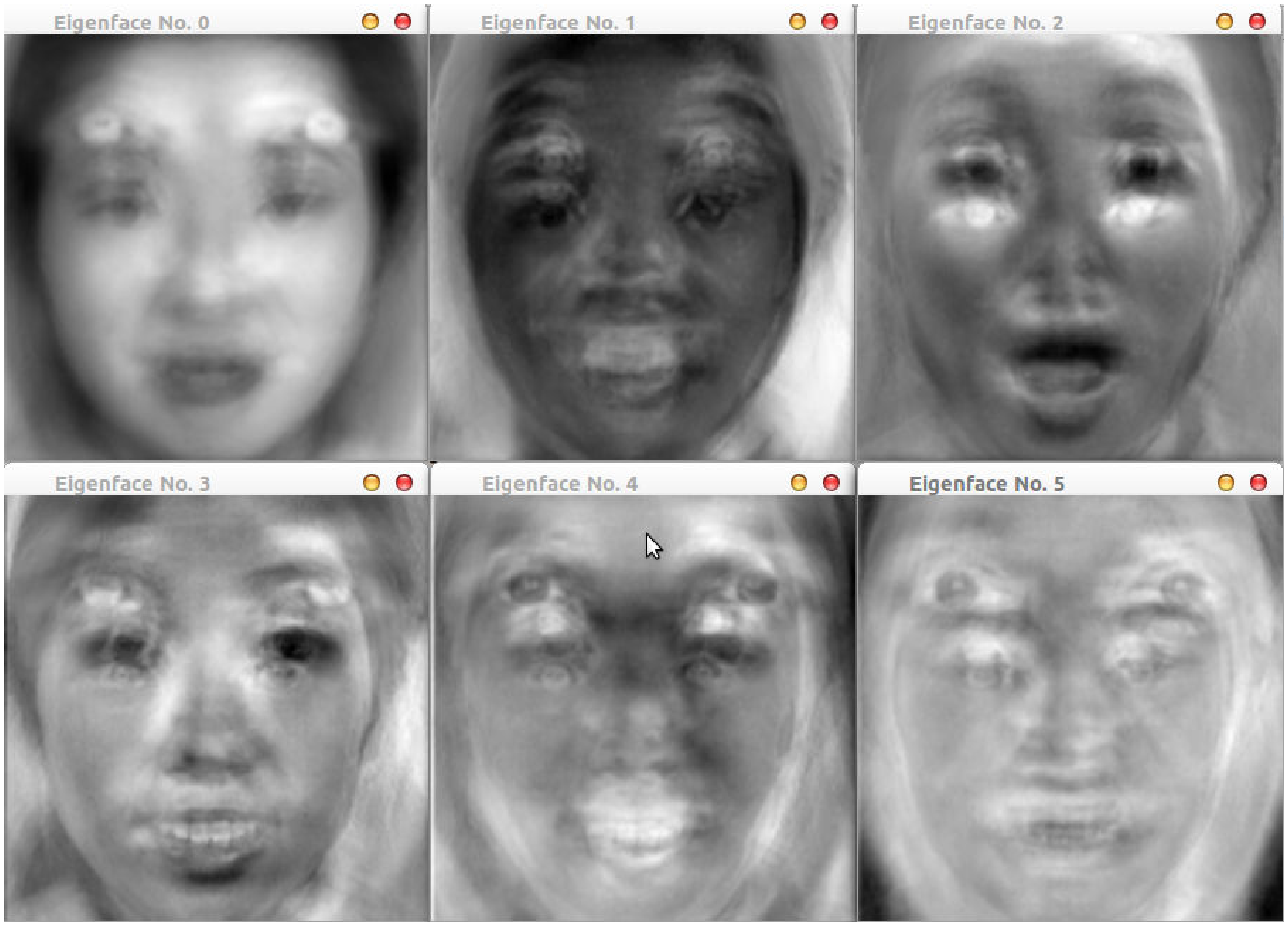


Figure 8: The first six eigenfaces computed from the face matrix

To describe any new image as a combination of eigenfaces, we need to project that image to the face-space formed by all eigenvectors. There are 97 images in the training set. Therefore, there are 97 eigenvectors or coordinates used to describe an image in the face-space.

```
[976.27423; 7257.1064; 1806.9884; -2526.3667; 181.47432; -38.718727; 1234.4166;
-237.55446; -425.2587; -62.171146; 22.951843; 769.17407; -21.172722; -1396.0421;
 774.461; 320.72742; 120.89563; 302.46585; 389.84717; -106.89835; 169.98007; 179
.55305; -94.023926; 91.572777; 383.0574; 1266.5129; 361.21939; -368.67856; -718.
35645; 263.21652; -345.83755; -317.13876; 200.35564; 137.68991; -199.47505; -455
.008; 29.709715; -547.48541; -114.33552; -422.96594; -70.525093; -45.015648; -30
4.44257; -28.045794; 617.23517; -252.65034; 124.59427; -30.084181; -350.65817; 2
53.90979; -136.38075; 103.90551; 303.75723; 6.2265906; -373.15509; 335.75708; -2
25.14496; 289.9335; -816.57965; -72.98452; 187.06352; -410.94208; -455.09003; -1
09.57374; -502.24417; 197.18393; -49.704887; 59.418995; -298.9852; -24.037497; 7
5.238762; -261.95013; -81.253716; -58.059063; 172.89392; -496.33405; 235.04984;
132.9686; -179.31104; -85.806129; 128.7023; 49.644699; 50.931923; 165.03949; -40
9.22269; 246.70923; -167.6434; -250.74562; 252.09904; 677.55115; 454.08633; 61.8
86051; -461.92508; -565.89813; -151.36044; 26.775919; 83.157188]
```

Figure 9: A set of weight obtained from projecting an image to the face-space.

As seen in the image above, an image projected to the face-space can be described as a combination of 97 eigenvectors as following:

$$I = 976.27423 * v_1 + 7257.1064 * v_2 + 1806.9884 * v_3 + \ldots\ldots + 83.157188 * v_{97}$$

in which v_i is the eigenvectors (or principle components) obtained from the face matrix. Any image needs only 97 weights to be described in the face-space. These weights also express the features contained in the image. For instance, the image used in this example has a large number equivalent to eigenvector 2. That means it contains more features described by eigenface 2. This example clearly shows the use of PCA in image compression and feature extraction.

5 Neural Network Training

While Principle Component Analysis (PCA) can help find similarities between images, and extract features from them, it doesn't necessarily mean that it can correctly determine which emotion is present in the image. For example, an image in the “happy” training set may be similar to another image in the “angry” set. Because of this, we may want images matching this “happy” image to also suggest that the subject may be “angry” instead. Additionally, subset of the “happy” faces, for example, may be more highly correlated to happiness than another, and so it may be beneficial to weight the to give the stronger connections more weight in the decision than the weaker connections.

One way to deal with these problems in a way that is compatible with the intention of the original PCA technique is to pair the output vector produced by the PCA with a neural network that is capable of learning these nuances in the data. This approach should result in a more accurate prediction on emotion than can be achieved with PCA alone.

Neural networks are computation methods that are inspired by the biological brain and one of its most fundamental building blocks: the neuron. In its overly simplistic form, an independent neuron receives inputs from either a handful, or hundreds or thousands of neurons. Based on the total sum of the inputs, the neuron will either fire, or will not fire, depending on if a threshold is reached. Not all of the inputs to the neuron are equal, however. Some will weigh more strongly on the outcome than others. Some will actually subtract from the total sum, instead of adding to it. The output signal then propagates to other neurons, through both electrical and chemical processes. Its impact on other neuron in the network are similarly weighted separately to each neuron it is connected to.

This basic model of the neuron is what forms the basis of the back propagation neural network, with some small changes. In this particular network, we have three layers of neurons, or processing elements (PEs). The first (input) layer of PEs, in this case, comes directly from the output of the PCA. The third, and final, layer is the output layer. Each PE in this layer corresponds to one of the seven emotions that we are training the neural network to identify.

The middle layer, called the “hidden” layer, is the second stage of processing that allows intermediate aspects of the analysis to be determined and stored, and therefore weighing on the final output. Every PE at the input layer is connected to every PE of the hidden layer. Every PE of the hidden layer is connected to every input at the output layer. At each stage, instead of an all-or-nothing firing strategy, PEs in a back propagation network will instead fire using a sigmoid function, so that low (or negative) values will result in an output close to -1 (or 0), and high values will result in a value close to 1. Values in between will map to their corresponding locations on the sigmoid curve. Each PE on the output will then fire with a magnitude of how “sure” the neural network is that the face being identified matches the recognizable emotions. The highest value is typically the response chosen, but the exact value may give any back end system an indication on whether the results are accurate enough for further action based on the results of the neural network analysis.

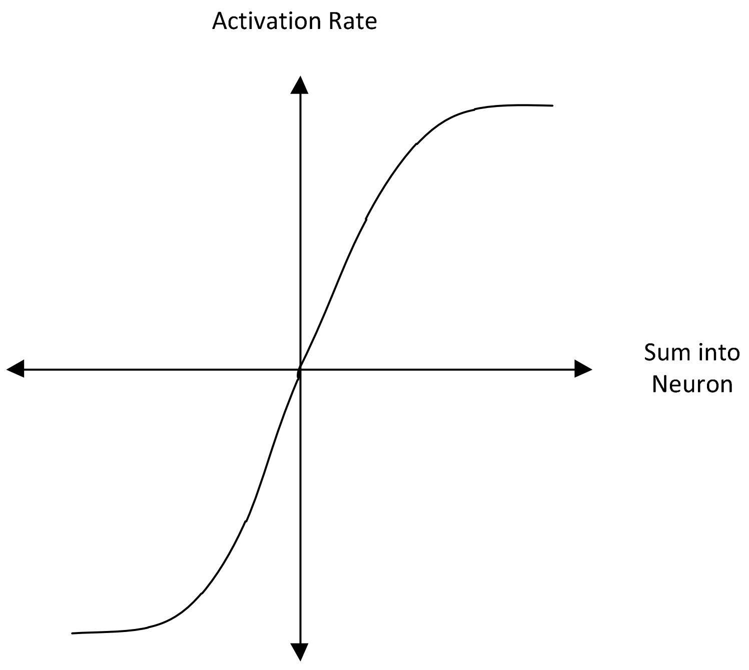


Figure 10: Example Activation Function based on sigmoid

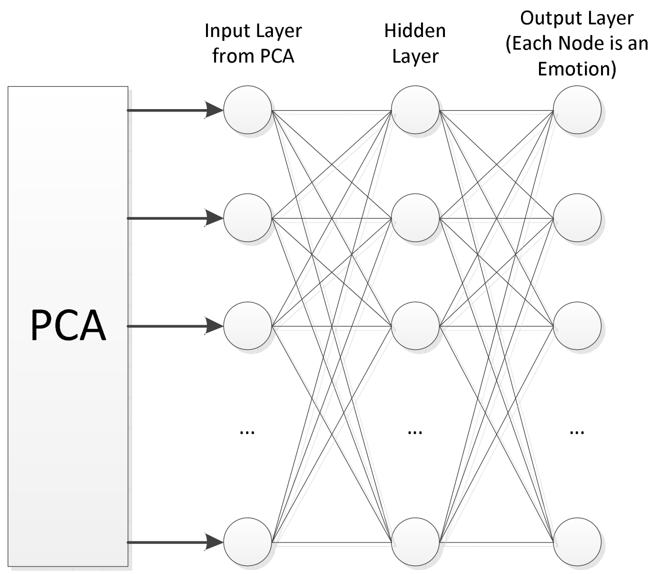


Figure 11: Basic architecture of PCA connected to Back Propagation Neural Network

If we randomize all of the connection weights of the network (which is typically the starting condition of most neural networks) passing an image through the PCA and then through the neural network will, of course, yield random results. Adjusting the weights so that the neural network yields expected results is called “training” the neural network. Training the network is typically the first of two steps of getting a neural network to respond as expected, the second is testing the neural network. Each step consists of running examples through the neural network, however only in the “training” phase we will adjust the weights of the network to bring the response closer to the expected value. We will run the “training” set hundreds, or even thousands of times, depending on the data, and then validate against a separate set of data (the “testing” set.) The reason for using separate data is to guarantee that the neural network trained the weights such that it is capable of interpreting data that it has never seen before (generalized learning), as opposed to simply “memorizing” the patterns it was trained on.

After each training example is presented to the neural network, the weights are adjusted such that the overall error of the response is reduced. Adjusting the weights between the hidden PEs and the output PEs is fairly straightforward. Simplified, we adjust each weight to each output by the error value (typically the square of the difference between the expected (1 if the emotion is expected, 0 if not), and actual value.) This error value is multiplied by the previous weight, because this is the proportion that this particular connection contributed to the error.

The reason we use the derivative to find the proper signal to change the weights may, at first, not be immediately clear. What we are attempting to do is calculate the weight change that will bring us closer to the weight value that reduces the error function as much as possible. To do this, we use derivative which will give us a rate of change of the function as compared to the weight in question. In other words, we operate “as if” the weight change will follow a gradient descent to reduce the overall error. From Haykin’s book “Neural Networks and Learning Machines”, we know that this rate of change can be expressed by calculus chain rule expansion as [6]:

$$\frac{\partial \varepsilon(n)}{\partial w_{ji}(n)} = \frac{\partial \varepsilon(n)}{\partial e_j(n)} \frac{\partial e_j(n)}{\partial y_j(n)} \frac{\partial y_j(n)}{\partial v_j(n)} \frac{\partial v_j(n)}{\partial w_{ji}(n)}$$

Equation 9: Chain Rule Expansion to Derive Learning Rule

Where ε is the error function, w_{ji} is the weight from neuron i to j, e_j is the expected output after summation and activation function into the node, y_j is the actual output, and v_j is the actual summation at neuron j.

After differentiating, and adding a learning rate coefficient, we end up with:

$$\Delta w_{ji} = \eta e_j(n) \varphi_j'(v_j(n)) y_i(n)$$

Equation 10: Delta Learning Rule

Where η is our learning coefficient (parameterized depending on problem), and $\varphi_j'(v_j(n))$ is the derivative of the activation function.

Number of hidden layers	Layer 1	Layer 2	Results
2	10	20	Obtain good results, known images close to what expected. Unknown images are predicted closely to final results.
1	5		Works good compared to previous results. Besides, using only one layer improves the processing speed.
1	20		The results obtained are about the same as using 5 neutrons in the hidden layer but the processing speed increases.

Table 4: Performance comparison between different choices of hidden layers and the number of neurons in the hidden layers.

As seen in the table above, we get good results using of only 1 hidden layer with 5 neurons. Keep increasing the number of layers or neurons doesn't have a significant impact on the final result but increasing the processing time. Therefore, we decided to use 1 hidden layer with 5 neurons in our neural network.

6 Kinect Interface

One of the challenges of the project was successfully interfacing with a Kinect Camera to gather frame information. What makes this a challenge is the fact that many parts of the final robotic system will need access to the same camera interface. The goal of the Kinect Interface code is to create an Application Programming Interface (API) that interfaces directly with the Kinect that could eventually by wrapped in an identical API that accesses the Kinect over a small LAN network (or network switch.) The idea behind this is creating a stable layer that does not eat a lot of system resources to get camera information, but is also thread-safe so that multiple programs can access the same resources, as well as prevent direct access to the camera, which helps keep the system stable by providing a single-point of entry to get access to the Kinect camera information (both the RGB video, as well as the depth information provided by the camera.)

An added benefit of this approach is that it frees up anyone who need to interface with the Kinect for future projects from having to develop code to access the device. Instead, they can simply call tested API calls that will abstract away implementation details, and easily yield OpenCV Mat data classes so that they can be easily manipulated from within the OpenCV framework.

The underlying architecture is a set of circular buffers. One buffer is for the RGB frame data from the Kinect, and the other is the depth image. (Only one buffer is shown in the diagram for clarity.) The depth image is simply a grayscale image, however, each pixel's value is representative of how far an object is from the Kinect, rather than information about its spectral characteristics. Whenever a new frame is available from the Kinect hardware, the program is interrupted to add another frame to the buffer after checking that the frame is no longer in use. Whenever a subsystem of the robot requires a new frame, the newest frame is given to them, but the buffer location is locked (except to other subsystems) until the frame has been successfully copied out.

The current number of frames in the buffer is 10, although this can be modified when the source code is compiled. (It is unlikely that the oldest frame will be in use when the Kinect has a new frame available, but synchronization is still required to prevent system crashes in the rare case that it does happen.)

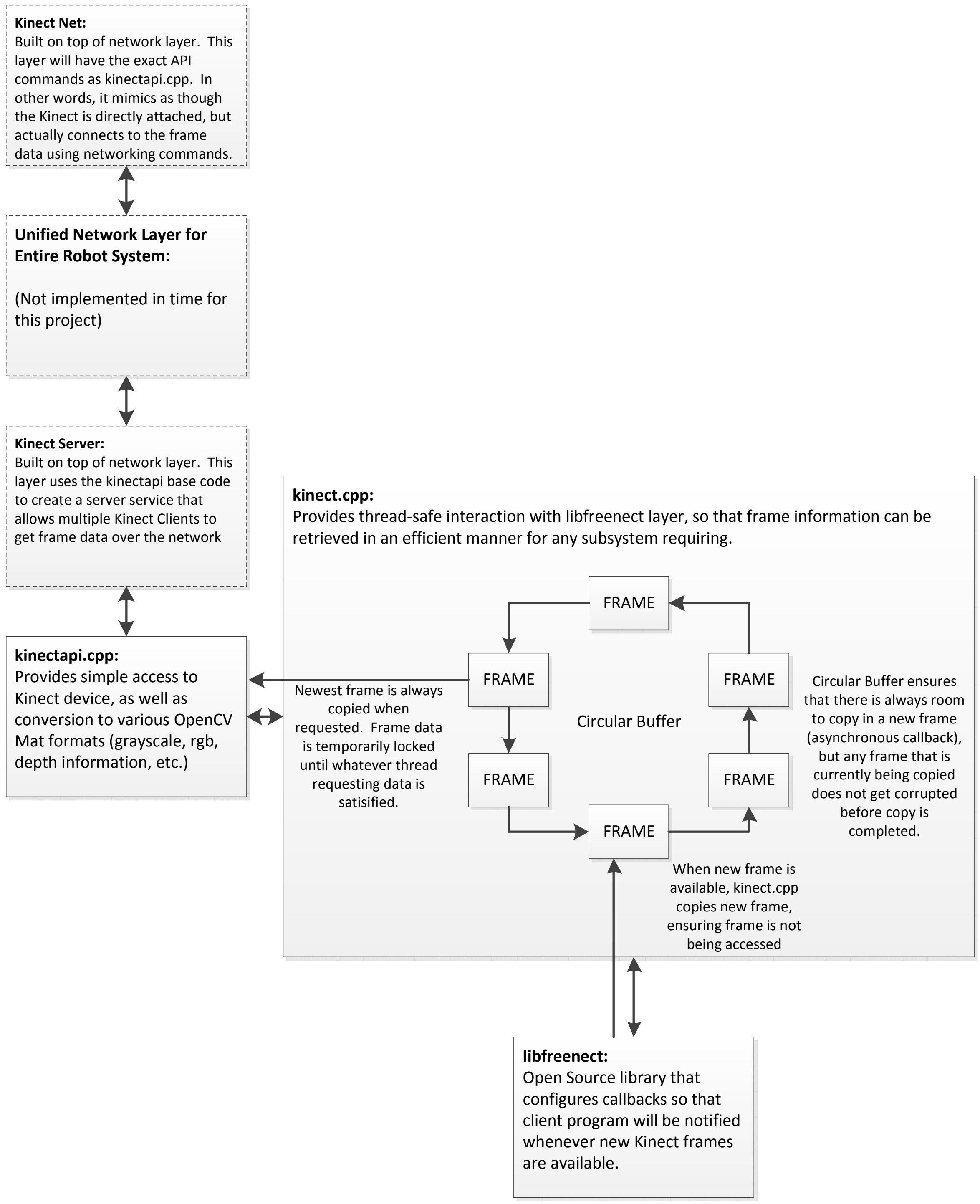

Kinect Net:
Built on top of network layer. This layer will have the exact API commands as kinectapi.cpp. In other words, it mimics as though the Kinect is directly attached, but actually connects to the frame data using networking commands.
Unified Network Layer for Entire Robot System:
(Not implemented in time for this project)
Kinect Server:
Built on top of network layer. This layer uses the kinectapi base code to create a server service that allows multiple Kinect Clients to get frame data over the network
kinectapi.cpp:
Provides simple access to Kinect device, as well as conversion to various OpenCV Mat formats (grayscale, rgb, depth information, etc.)
kinect.cpp:
Provides thread-safe interaction with libfreenect layer, so that frame information can be retrieved in an efficient manner for any subsystem requiring.
FRAME
Circular Buffer
Newest frame is always copied when requested. Frame data is temporarily locked until whatever thread requesting data is satisified.
Circular Buffer ensures that there is always room to copy in a new frame (asynchronous callback), but any frame that is currently being copied does not get corrupted before copy is completed.
When new frame is available, kinect.cpp copies new frame, ensuring frame is not being accessed
libfreenect:
Open Source library that configures callbacks so that client program will be notified whenever new Kinect frames are available.

Figure 12: Architecture of Kinect Interface, and suggestion for future expansion.

To use the interface, you simply need to include the kinectapi.h header file, and then create a kinectinterface object.

```
kinectinterface interface();
```

Then, you can use the following API commands to get the latest frame images. For example, you can get a 8-bit grayscale video image by doing the following:

```
Mat * gray8 = interface.get8BitGrayscale();
```

The interfacing routines to get OpenCV matrices from the Kinect are written in a way that abstracts away the implementation details. This was done to allow these APIs to be ported to other system configurations. In particular, it was written to allow multiple systems to connect to a server that feeds out frame information to these devices. This can be implemented by writing a server, that will be written for an underlying network layer, that accesses the Kinect directly using the kinectapi source code (Kinect Server). This will allow devices to connect to it, and then feed frame data over the network as required. In this way, the only program getting access to the Kinect directly is the Kinect Server. Other devices can then use code that has an identical API to the kinectapi code, but then are wrappers for communication with the Kinect Server. The end goal of this would be to allow programs to run identically regardless of whether the Kinect was directly attached, or if the Kinect was actually connected to an entirely different device.

API Call	Description
Mat * get8BitRGB();	Return a pointer to the latest RGB frame (8 bits per color) available from the Kinect. The pointer is valid until get8BitRGB() is called again.
Mat * get16BitDepth();	Return a pointer to the latest depth frame, w/ 16 bits of information per pixel. The pointer is valid until get16BitDepth() is called again.
Mat * get8BitDepth();	Return a pointer to the latest depth frame, w/ 8 bits of information per pixel. The pointer is valid until get8BitDepth() is called again.
Mat * get8BitGrayscale();	Return a pointer to the latest video frame (8 bits grayscale information per pixel) available from the Kinect. The pointer is valid until get8BitGrayscale () is called again.
Mat * get16BitGrayscale();	Return a pointer to the latest video frame (16 bits grayscale information per pixel) available from the Kinect. The pointer is valid until get16BitGrayscale () is called again.
uint32_t getLastTimestamp();	Get the timestamp from the very last function get* function called
int getLastFrameNum();	Get the frame count number from the very last function get* function called. NOTE: It is possible for depth and video frames to drift slightly from each other on a running system.

Table 5: Generalized OpenCV Kinect API

7 Future Expansions of Project

While much was done this term, there is still lots of room for future expansion of this project. First of all, the larger the dataset of human face images that are available, the more accurate the algorithm could be. As of the writing of this report, the images available were very limited, and we were unable to get access to the larger databases available for academia with enough time to use them in our algorithm. Once these new images are obtained, it would then be possible to further tune the neural network portion of the algorithm. We can adjust the learning coefficient of the system, the momentum terms, number of hidden nodes, number of training iterations, etc., until we find the weights that lead to the most accurate emotion recognition. Once this is done, we can save the weights so that the neural network does not have to be retrained during operating mode.

Another place with room for expansion is the Kinect interface. The networking layer that will be available to all components of the final robotic system was not ready in time for a Kinect Server and Kinect Client software to be written. These components would be relatively quick to develop and implement, and could produce a backbone for any component in the final system that requires image information (video or depth) from the Kinect in a manner that improves overall system stability.

Additionally, it might be possible to use the depth information in parallel with the video frame information in emotion recognition. If a database of depth image faces could be produced, it might be possible to implement the PCA algorithm on the new dataset, and have these be additional inputs to the NN for training and operation mode.

8 Project Conclusions

By the end of this project, a system that could read data from the Kinect, and then recognize human emotion characteristics was created. There is much room form improvement when larger emotion test sets are introduced, and potentially there is room for improvement if depth images are introduced to the PCA algorithm, so that more information can be used to characterize a person’s facial expressions to determine emotion.

The PCA algorithm seemed to work really well, and very quickly, to extract elements of people’s faces to determine an emotion set. Using live camera data, it recognized easy emotions such as “happiness”, when we smiled into the camera. The neural network was very efficient as well, despite the fact that more training/tuning may be required once the test set is expanded.

While much work is required to make the solution more robust, and ready to be implemented in a live robotic system, much of the heavy lifting has been done, and the framework has been laid for future students to take on this project, expand it, refine it, and then finally implement it.

Appendix A Installing OpenCV and OpenKinect

OpenCV, and libfreenect, can easily be installed on a Ubuntu system. Please note that these instructions are for OpenCV version *2.1* on a Ubuntu 11.10 system. This is the version of OpenCV that is considered stable by Ubuntu, as of this writing, and is checked into the Ubuntu distribution system. Version 2.3 is also available, but the installation instructions are not as simple, and are not covered here. The source code for this project should work with OpenCV version 2.3, but this compatibility is not guaranteed—some minor porting may be required. Also note that the libfreenect installation instructions may change. Please visit www.openkinect.org for the latest installation instructions.

To install OpenCV 2.1 on a Ubuntu machine, simply type the following command (one line):

```
sudo apt-get install libcv-dev libcv2.1 libcvaux-dev libcvaux2.1 libhighgui-dev
libhighgui2.1
```

Libfreenect, the library used to interface with the camera, can be installed using the following commands:

```
sudo add-apt-repository ppa:floe/libtisch
sudo apt-get update
sudo apt-get install libfreenect libfreenect-dev libfreenect-demos
sudo adduser $USER video
```

Appendix B PCA and NN Source Code

cFaceRecognizer.h

```
#ifndef __FACERECOGNIZER_H__
#define __FACERECOGNIZER_H__

#include <iostream>
#include <vector>
#include <float.h>
#include <cv.h>

using namespace std;
using namespace cv;
class FaceRecognizer {

public:
	FaceRecognizer(const Mat& trFaces, const vector<int>& trImageIDToSubjectIDMap);
	~FaceRecognizer();
	void init(const Mat& trFaces, const vector<int>& trImageIDToSubjectIDMap);
	int recognize(const Mat& instance);
	Mat getWeight(const Mat& testImage);
	Mat getAverage();
	Mat getEigenvectors();
	Mat getEigenvalues();

private:
	PCA *pca;
	vector<Mat> projTrFaces;
	vector<int> trImageIDToSubjectIDMap;
};

#endif
```

NeuNet.h

```
/*
 * NeuNet.h
 *
 *  Created on: Feb 7, 2012
 *      Author: hoang
 */

#ifndef NEUNET_H_
#define NEUNET_H_

#include <opencv2/core/core.hpp>
#include <opencv2/highgui/highgui.hpp>

//required for multilayer perceptrons
#include<opencv2/ml/ml.hpp>
using namespace cv;

class cANN
{

public:
	CvANN_MLP ann;
    void trANN(const Mat& trainingData, const Mat& trainingResults)             //
Traing the Neural Net
```

```
    {
        cv::Mat layers = cv::Mat(3, 1, CV_32SC1); //create 3 layers

        layers.row(0) = cv::Scalar(trainingData.cols); //input layer accepts the
weights of input images
        layers.row(1) = cv::Scalar(5);//hidden layer
        //layers.row(2) = cv::Scalar(10);//hidden layer
        layers.row(2) = cv::Scalar(7); //output layer returns to one of 7 emotions

        //ANN criteria for termination
        CvTermCriteria criter;
        criter.max_iter = 200; // *********change 100 to 200 for experiment**********
        criter.epsilon = 0.00001f;
        criter.type = CV_TERMCRIT_ITER | CV_TERMCRIT_EPS;

        //ANN parameters
        CvANN_MLP_TrainParams params;
        params.train_method = CvANN_MLP_TrainParams::BACKPROP;
        params.bp_dw_scale = 0.05f;
        params.bp_moment_scale = 0.05f;
        params.term_crit = criter; //termination criteria

        ann.create(layers);
        // train
        ann.train(trainingData, trainingResults, cv::Mat(), cv::Mat(), params);
    }

    Mat teANN(const Mat& testingData)
    {
        Mat predicted(testingData.rows, 7, CV_32FC1); // Row is the number of testing
images, Column is emotions recognized

        for(int i = 0; i < testingData.rows; i++)
        {
            Mat response = predicted.row(i);
            Mat sample = testingData.row(i);

            ann.predict(sample, response);
        }

//        std::cout << predicted << std::endl;
        return predicted;
    }


};

#endif /* NEUNET_H_ */
```

cFaceRecognizer.cpp

```
#include "cFaceRecongizer.h"

FaceRecognizer::FaceRecognizer(const Mat& trFaces, const vector<int>&
trImageIDToSubjectIDMap)
{
       init(trFaces, trImageIDToSubjectIDMap);
}

void FaceRecognizer::init(const Mat& trFaces, const vector<int>&
trImageIDToSubjectIDMap)
{
	int numSamples = trFaces.cols;
	this->pca = new PCA(trFaces, Mat(),CV_PCA_DATA_AS_COL);

	for(int sampleIdx = 0; sampleIdx < numSamples; sampleIdx++) {
		this->projTrFaces.push_back(pca->project(trFaces.col(sampleIdx)));
	}

	this->trImageIDToSubjectIDMap = trImageIDToSubjectIDMap;
}

FaceRecognizer::~FaceRecognizer()
{
	delete pca;
}

int FaceRecognizer::recognize(const Mat& unknown)
{
	// Take the vector representation of unknown's face image and project it
	// into face space.
	Mat unkProjected = pca->project(unknown);

	// I now want to know which individual in my training data set has the shortest
distance
	// to unknown.
	double closestFaceDist = DBL_MAX;

	int closestFaceID = -1;
	for(unsigned int i = 0; i < projTrFaces.size(); i++) {
		// Given two vectors and the NORM_L2 type ID the norm function computes
the Euclidean distance:
		//     dist(SRC1,SRC2) = SQRT(SUM(SRC1(I) - SRC2(I))^2)
		// between the projections of the current training face and unknown.
		Mat src1 = projTrFaces[i];
		Mat src2 = unkProjected;
		double dist = norm(src1, src2, NORM_L2);

		// Every time I find somebody with a shorter distance I save the
distance, map his
		// index number to his actual ID in the set of traing images and save the
actual ID.
		if(dist < closestFaceDist) {
			closestFaceDist = dist;
			closestFaceID = this->trImageIDToSubjectIDMap[i];
		}
	}
	return closestFaceID;
}

// Project a test image to face-space and get its weight
Mat FaceRecognizer::getWeight(const Mat& testImage)
{
	return pca->project(testImage);
}
// Returns the vector containing the average face.
Mat FaceRecognizer::getAverage()
{
	return pca->mean;
}


// Returns a matrix containing the eigenfaces.
Mat FaceRecognizer::getEigenvectors()
{
       return pca->eigenvectors;
}

// Returns a matrix containing the eigenvalues.
Mat FaceRecognizer::getEigenvalues()
{
       return pca->eigenvalues;
}
```

EmoRegByAnn.cpp

```
#include <cv.h>
#include <highgui.h>
#include "objdetect/objdetect.hpp"
#include "imgproc/imgproc.hpp"
#include "highgui/highgui.hpp"

#include <iostream>
#include <sstream>
#include <fstream>
#include <string>
#include <vector>

#include "cFaceRecongizer.h"
#include "NeuNet.h"
//#include "kinectapi.h"


using namespace std;
using namespace cv;


// Test lists consist of the subject ID of the person of whom a face image is and the
// path to that image.
void readFile(const string& fileName, vector<string>& files, vector<int>&
indexNumToSubjectIDMap)
{
       while (!files.empty())
       {
              files.pop_back();          // empty this vector before adding anything to
it,
                                                      // to make sure there's no
repetitive info in this vector
       }

       std::ifstream file(fileName.c_str(), ifstream::in);

       if(!file) {
              cerr << "Unable to open file: " << fileName << endl;
              exit(0);
       }

       std::string line, path, trueSubjectID;
       while (std::getline(file, line)) {
              std::stringstream liness(line);
              std::getline(liness, trueSubjectID, ';');
              std::getline(liness, path);

              path.erase(std::remove(path.begin(), path.end(), '\r'), path.end());
              path.erase(std::remove(path.begin(), path.end(), '\n'), path.end());
              path.erase(std::remove(path.begin(), path.end(), ' '), path.end());
```

```
            files.push_back(path);
            indexNumToSubjectIDMap.push_back(atoi(trueSubjectID.c_str()));
      }
}


void unableToLoad()
{
      cerr << "Unable to load face images. The program expects a set of face images
in a subdirectory" << endl;
      cerr << "of the execution directory named 'att_faces'. This face database can
be freely downloaded " << endl;
      cerr << "from the Cambridge University Copmputer Lab's website:" << endl;
      cerr << "
http://www.cl.cam.ac.uk/research/dtg/attarchive/facedatabase.html" << endl;
      exit(1);
}

int main(int argc, char *argv[])
{
      // Defining variables
      vector<string> teFaceFiles;
      vector<int> teImageIDToSubjectIDMap;
      vector<string> trFaceFiles;
      vector<int> trImageIDToSubjectIDMap;
      double duration1(0), duration2(0), duration3(0); // These variables used to
evaluate the performace of PCA and NN

      string trainingList = "./train_original.txt";
      string testList = "./test_original.txt";

      string face_cascade_name = "haarcascade_frontalface_alt.xml";      // Cascade
classifier used for face tracking
      CascadeClassifier face_cascade;
      // Define an instance of class face_cascade used for tracking face
      if( !face_cascade.load( face_cascade_name ) )                            //
Load Cascade classifier
      {
            printf("--(!)Error loading\n");
            return -1;
      };


      // Read training dataset
      readFile(trainingList, trFaceFiles, trImageIDToSubjectIDMap);

      Mat teImg = imread(trFaceFiles[0], 0);
      Mat trImg = imread(trFaceFiles[0], 0);

      if(trImg.empty())
      {
            unableToLoad();
      }


      // Eigenfaces operates on a vector representation of the image so we calculate
the
      // size of this vector.  Now we read the face images and reshape them into
vectors
      // for the face recognizer to operate on.
      int imgVectorSize = teImg.cols * teImg.rows;
```

```
	// Create a matrix that has 'imgVectorSize' rows and as many columns as there
are 		images.
	Mat trImgVectors(imgVectorSize, trFaceFiles.size(), CV_32FC1);
	// Load the vector.
	for(unsigned int i = 0; i < trFaceFiles.size(); i++)
	{
		Mat tmpTrImgVector = trImgVectors.col(i);
		Mat tmp_img;
		imread(trFaceFiles[i], 0).convertTo(tmp_img, CV_32FC1);
		tmp_img.reshape(1, imgVectorSize).copyTo(tmpTrImgVector);
	}

	//******************************Training
phase*****************************************
	// On instantiating the FaceRecognizer object automatically processes
	// the training images and projects them.

	// Evaluate the time needed for PCA implementation
	duration1 = static_cast<double>(cv::getTickCount());

	FaceRecognizer fr(trImgVectors, trImageIDToSubjectIDMap);
	duration1 = static_cast<double>(cv::getTickCount()) - duration1;
	duration1 /= cv::getTickFrequency();

	/////////////Initialize Input Layer for Neural Network/////////////////////
	// Loop through all training images and get the weights of each of them;
	// Put these weights into a Matrix used for training Neural Network

	// Evaluate the time needed for training NN
	duration2 = static_cast<double>(cv::getTickCount());

	Mat temp;
	trImg.convertTo(temp, CV_32FC1);
	Mat weight_temp = fr.getWeight(temp.reshape(1, imgVectorSize));  // The weights
of each image is described in one row instead of column
	Mat trainingData(trFaceFiles.size(), weight_temp.rows, CV_32FC1,
Scalar::all(0));    // Initialize a Matrix to store all training weights
	for (unsigned int i=0; i<trFaceFiles.size(); i++)
	{
		Mat temp = trainingData.row(i);
		Mat temp1;
		imread(trFaceFiles[i],0).convertTo(temp1, CV_32FC1);
		Mat weight_temp = fr.getWeight(temp1.reshape(1, imgVectorSize));
		weight_temp.reshape(1, 1).copyTo(temp); // Change the format of the
weight so it can fit in one traingData row
	}


	//////////Initialize Output Layer for Neural Network/////////////////
	Mat trainingResults(trFaceFiles.size(), 7, CV_32FC1, Scalar::all(0));    // Row
is the number of training images,

					// Column is equivalent 7 emotions
	for (unsigned int i=0; i < trFaceFiles.size(); i++)
	{
		switch(trImageIDToSubjectIDMap[i])
		{
		case 1: // Sad
			trainingResults.at<float>(i,0) = 1;
			break;
		case 2: // Angry
			trainingResults.at<float>(i,1) = 1;
			break;
```

```
            case 3: // Digust
                  trainingResults.at<float>(i,2) = 1;
                  break;
            case 4: // Neutral
                  trainingResults.at<float>(i,3) = 1;
                  break;
            case 5: // Fear
                  trainingResults.at<float>(i,4) = 1;
                  break;
            case 6: // Surprise
                  trainingResults.at<float>(i,5) = 1;
                  break;
            case 7: // Happy
                  trainingResults.at<float>(i,6) = 1;
                  break;
            }
      }

      // Implement Neural Network
      cANN emoANN;

      // Train the NeuralNet with trainingData and trainingResults
      emoANN.trANN(trainingData, trainingResults);
      duration2 = static_cast<double>(cv::getTickCount()) - duration2;
      duration2 /= cv::getTickFrequency();
      cout << "Training complete!!!" << endl;


      //****************************Testing phase*******************************//
      // Use Neural Network to evaluate the testing image
      // Initialize a Matrix to store all weights of test images

      //kinectinterface interface; // an instace of kinect interface, used to capture
frames from kinect, uncomment this to capture image from Kinect
      //Mat* grayimg;
      CvCapture* capture;
      Mat frame, gray_frame;
      capture = cvCaptureFromCAM( -1 );

      while (1)
      {
      // Evaluate time needed for testing an image using NN
//    readFile(testList, teFaceFiles, teImageIDToSubjectIDMap);
//    duration3 = static_cast<double>(cv::getTickCount());

/* This part is used to test individual images */
//    Mat testingData(teFaceFiles.size(), weight_temp.rows, CV_32FC1,
Scalar::all(0));
//    for (unsigned int i=0; i<teFaceFiles.size(); i++)
//    {
//          Mat temp = testingData.row(i);
//          Mat temp1;
//          imread(teFaceFiles[i],0).convertTo(temp1, CV_32FC1);
//          Mat weight_temp = fr.getWeight(temp1.reshape(1, imgVectorSize));
//          weight_temp.reshape(1, 1).copyTo(temp); // Change the format of the
weight so it can fit in one traingData row
//    }


      // Testing an image captured from Kinect, uncomment this to capture frame from
Kinect
//    grayimg = interface.get8BitGrayscale();
//    Mat gray_frame = *grayimg;
```

```
	// Testing an image captured from normal video
	frame = cvQueryFrame( capture );
	cvtColor( frame, gray_frame, CV_BGR2GRAY );
	equalizeHist( gray_frame, gray_frame );

	// Face tracking using face cascade classifier
	vector<Rect> faces; // define a vector to contain faces info from Face tracking
classifier
	face_cascade.detectMultiScale( gray_frame, faces, 1.1, 2,
0|CV_HAAR_SCALE_IMAGE, Size(100, 100) );
	for (int i = 0; i<faces.size(); i++)
	{
		Point top_left(faces[i].x, faces[i].y + 20);
		Point top_right(faces[i].x + faces[i].width, faces[i].y + faces[i].height
+ 20);
		rectangle(gray_frame, top_left, top_right, Scalar( 255, 0, 255 ));
		Mat faceROI = gray_frame(Rect(faces[i].x, faces[i].y+20, faces[i].width ,
faces[i].height));  // define Region of Interest
		Mat faceROI_resized(Size(150,150), CV_8UC3);
						// Resize ROI to 150x150
		resize(faceROI, faceROI_resized, faceROI_resized.size(), 0, 0,
INTER_NEAREST);		// faceROI_resized is the image which will be projected to
eigenface
		// End of face tracking

		Mat testingData(1,weight_temp.rows,CV_32FC1,Scalar::all(0)); //
testingData only contains one image captured from Kinect at a time
		Mat temp = testingData.row(0);
		Mat temp1;
		faceROI_resized.convertTo(temp1, CV_32FC1);
		Mat weight_temp = fr.getWeight(temp1.reshape(1, imgVectorSize));
		weight_temp.reshape(1, 1).copyTo(temp); // Change the format of the
weight so it can fit in one traingData row
		Mat results = emoANN.teANN(testingData);

		// Display frames
//	duration3 = static_cast<double>(cv::getTickCount()) - duration3;
//	duration3 /= cv::getTickFrequency();

	// Evaluate test results, display only expressions have probability greater
than 20%
		for (int i = 0; i<results.rows; i++)
		{
			cout << "Picture " << i + 1 << ":" << endl;
			for (int j = 0; j<results.cols; j++)
			{
				float temp = results.at<float>(i,j);
				if (temp >= 0.2)
				{
					if (temp >=1) temp = 1;
					switch (j)
					{
					case 0: cout << "\t" << temp*100 << "% Sad." << endl;
							break;
					case 1: cout << "\t" << temp*100 << "% Angry." <<
endl;
							break;
					case 2: cout << "\t" << temp*100 << "% Disgust." <<
endl;
							break;
					case 3: cout << "\t" << temp*100 << "% Neutral." <<
endl;
```

```
                                        break;
                                case 4: cout << "\t" << temp*100 << "% Fear." <<
endl;
                                        break;
                                case 5: cout << "\t" << temp*100 << "% Surprise." <<
endl;
                                        break;
                                case 6: cout << "\t" << temp*100 << "% Happy." <<
endl;
                                        break;
                                }
                        }
                }
            }
            imshow("Frame", gray_frame);
            imshow("Face", faceROI_resized);
            cv::waitKey(5);
    }
    }

//      cout << "Time used for implementing PCA: " << duration1 << " s." << endl;
//      cout << "Time used for training NN: " << duration2 << " s." << endl;
//      cout << "Time used for evaluating an image using NN: " << duration3 << " s." <<
endl;
}
```

Appendix C Kinect Interface Source Code

Makefile

```
#Basic Compiler info
CPP=g++
#CFLAGS=-O2
CFLAGS=-g
#CFLAGS=

# Kinect module details
kinect_src=kinect.cpp
kinect_header=kinect.h
KINECT_LIB_OBJ=kinect.o
SO_PREFIX=libkinect
MAJOR_VER=0
MINOR_VER=1
SONAME=$(SO_PREFIX).so.$(MAJOR_VER)
KINECT_SHARED_NAME=$(SONAME).$(MINOR_VER)
OPEN_CV=`pkg-config --cflags opencv` `pkg-config --libs opencv`

KINECT_API_OBJ=kinectapi.o
KINECT_API_SRC=kinectapi.cpp
KINECT_API_HEADER=kinectapi.h
KINECT_LIB=$(SO_PREFIX).so

#General
libraries=-lfreenect #-lcv -lcxcore
INCLUDE=-I/usr/local/include/libfreenect -L.

#Unit Test Program
test_src=testkinect.cpp
TEST_EXE=test

all: $(KINECT_LIB_OBJ) $(KINECT_API_OBJ) $(KINECT_LIB) $(TEST_EXE) Makefile

$(KINECT_LIB_OBJ): $(kinect_src) $(kinect_header) Makefile
	$(CPP) $(INCLUDE) $(CFLAGS) -fPIC -shared $(OPEN_CV) $(kinect_src)  -c -o
$(KINECT_LIB_OBJ)

$(KINECT_API_OBJ): $(KINECT_API_SRC) $(KINECT_API_HEADER) Makefile
	$(CPP) $(INCLUDE) $(CFLAGS) -fPIC -shared $(OPEN_CV) $(KINECT_API_SRC)  -c -o
$(KINECT_API_OBJ)

$(KINECT_LIB): $(KINECT_LIB_OBJ) $(KINECT_API_OBJ) Makefile
	$(CPP) $(INCLUDE) -fPIC -shared -Wl,-soname,$(SONAME) $(KINECT_LIB_OBJ)
$(KINECT_API_OBJ) $(libraries) $(OPEN_CV) -o $(KINECT_SHARED_NAME)
	rm -f $(SO_PREFIX).so
	ln -sf $(KINECT_SHARED_NAME) $(SO_PREFIX).so

$(TEST_EXE): $(KINECT_LIB) $(test_src)  Makefile
	$(CPP) $(INCLUDE) $(CFLAGS) $(test_src)  -o $(TEST_EXE) $(OPEN_CV) $(libraries)
-lkinect

clean:
	rm -f $(TEST_EXE) $(KINECT_LIB_OBJ)
	rm -f $(SO_PREFIX).so
	rm -f $(KINECT_SHARED_NAME)
	rm -f $(KINECT_API_OBJ)
```

kinect.h

```
#ifndef KINECT_H
#define KINECT_H

#include <stdio.h>
#include <vector>
#include <opencv/cv.h>
#include <opencv/cxcore.h>
#include <opencv/highgui.h>

#include <unistd.h>

using namespace std;
using namespace cv;

#include <libfreenect.hpp>
//#include <libfreenect.h>

#define X_DIM                     640
#define Y_DIM                     480
#define FREENECT_DEPTH_11BIT_SIZE sizeof(uint16_t)*X_DIM*Y_DIM
#define FREENECT_VIDEO_RGB_SIZE         sizeof(uint8_t)*X_DIM*Y_DIM//*3
#define MAX_FRAMES                10

class Mutex {
   public:
      Mutex()
      {
         pthread_mutex_init( &mutex, NULL );
      }
      void lock()
      {
         pthread_mutex_lock( &mutex );
      }
      void unlock()
      {
         pthread_mutex_unlock( &mutex );
      }
   private:
      pthread_mutex_t mutex;
};

class frameData
{
   public:
      frameData()
      {
         frameNum = 0;
         timestamp = 0;
      }
      int frameNum;
      uint32_t timestamp;
      Mat * data;
};

class rgbFrame: public frameData {
   public:
      rgbFrame()
      {
         data = new Mat(Size(640,480),CV_8UC3,Scalar(0));
      }
      ~rgbFrame()
      {
         delete data;
      }
};

class grayscaleFrame: public frameData {
   public:
      grayscaleFrame()
      {
         data = new Mat(Size(640,480),CV_8UC1,Scalar(0));
      }
      ~grayscaleFrame()
      {
         delete data;
      }
};

class grayscale16BitFrame: public frameData {
   public:
      grayscale16BitFrame()
      {
         data = new Mat(Size(640,480),CV_16UC1,Scalar(0));
      }
      ~grayscale16BitFrame()
      {
         delete data;
      }
};

class depthFrame16Bit: public frameData {
   public:
      depthFrame16Bit()
      {
         data = new Mat(Size(640,480),CV_16UC1);
      }
      ~depthFrame16Bit()
      {
         delete data;
      }
};

class depthFrame8Bit: public frameData {
   public:
      depthFrame8Bit()
      {
         data = new Mat(Size(640,480),CV_8UC1);
      }
      ~depthFrame8Bit()
      {
         delete data;
      }
};

class KinectOpenCVDevice : public Freenect::FreenectDevice
{
   public:
      KinectOpenCVDevice(_freenect_context *_ctx, int _index)
         : Freenect::FreenectDevice(_ctx, _index),
buffer_depth(FREENECT_DEPTH_11BIT_SIZE),buffer_rgb(FREENECT_VIDEO_RGB_SIZE),
gamma(2048), depthMat(Size(640,480),CV_16UC1),
rgbMat(Size(640,480),CV_8UC3,Scalar(0)), ownMat(Size(640,480),CV_8UC3,Scalar(0))
      {
         for( unsigned int i = 0 ; i < 2048 ; i++) {
            float v = i/2048.0;
            v = std::pow(v, 3)* 6;
            gamma[i] = v*6*256;
         }
         rgb_frameNum = 0;
         depth_frameNum = 0;
      }

     void VideoCallback(void* _rgb, uint32_t timestamp);
     void DepthCallback(void* _depth, uint32_t timestamp);
     bool getVideo(frameData& output);
     bool getDepth(depthFrame16Bit& output);
     bool getDepth8(depthFrame8Bit& output);
     void resetCounts();

   private:
      std::vector<uint16_t> buffer_depth;
      std::vector<uint8_t> buffer_rgb;
      std::vector<uint16_t> gamma;
      Mat depthMat;
      Mat rgbMat;
      Mat ownMat;

      int rgb_frameNum;
      int depth_frameNum;
      int rgb_readCount[MAX_FRAMES];
      int depth_readCount[MAX_FRAMES];

      rgbFrame rgb_frames[MAX_FRAMES];
      depthFrame16Bit depth_frames[MAX_FRAMES];

      Mutex rgb_frameNumLock;
      Mutex depth_frameNumLock;
      Mutex rgb_readCountLock[MAX_FRAMES];
      Mutex depth_readCountLock[MAX_FRAMES];
      Mutex rgb_readLock[MAX_FRAMES];
      Mutex depth_readLock[MAX_FRAMES];

};

int boo (void);

#endif
```

kinectapi.h

```
#include "kinect.h"

class kinectinterface {
   public:
      kinectinterface();
      ~kinectinterface();
      Mat * get8BitRGB();
      Mat * get16BitDepth();
      Mat * get8BitDepth();
      Mat * get8BitGrayscale();
      Mat * get16BitGrayscale();
      uint32_t getLastTimestamp() {
         return lastTimestamp;
      };
      int getLastFrameNum() {
         return lastFrameNum;
      }

   private:
      rgbFrame rgb;
      depthFrame16Bit depth16;
      depthFrame16Bit depth16Temp;
      depthFrame8Bit depth8;
      rgbFrame rgbTemp;
      grayscaleFrame grayscale;
      grayscale16BitFrame grayscale16;
      uint32_t lastTimestamp;
      int lastFrameNum;
};
```

kinect.cpp

```
#include "kinect.h"


void KinectOpenCVDevice::VideoCallback(void* _rgb, uint32_t timestamp)
{
   // Lock frame count reference, then increment frame number.  Grab lock for frame
data.
   rgb_frameNumLock.lock();
   rgb_frameNum = rgb_frameNum + 1;
   int frame = rgb_frameNum;
   int id = frame%MAX_FRAMES;
   rgb_readLock[id].lock();
   rgb_frameNumLock.unlock();

   // Copy matrix data
   uint8_t* rgb = static_cast<uint8_t*>(_rgb);
   rgbMat.data = rgb;
   rgb_frames[id].frameNum = frame;
   rgbMat.copyTo(*rgb_frames[id].data);
   rgb_frames[id].timestamp = timestamp;

   // Unlock frame
   rgb_readLock[id].unlock();
   //printf("R_FRAME %d captured\n", rgb_frameNum);
   return;
}

void KinectOpenCVDevice::DepthCallback(void* _depth, uint32_t timestamp)
{
   // Lock frame count reference, then increment frame number.  Grab lock for frame
data.
   depth_frameNumLock.lock();
   depth_frameNum = depth_frameNum + 1;
   int frame = depth_frameNum;
   int id = frame%MAX_FRAMES;
   depth_readLock[id].lock();
   depth_frameNumLock.unlock();

   // Copy matrix data
   uint16_t* depth = static_cast<uint16_t*>(_depth);
   depthMat.data = (uchar*) depth;
   depth_frames[id].frameNum = frame;
   depthMat.copyTo(*depth_frames[id].data);
   depth_frames[id].timestamp = timestamp;
   // Unlock frame
   depth_readLock[id].unlock();
   //printf("D_FRAME %d captured\n", depth_frameNum);
   return;
}

bool KinectOpenCVDevice::getVideo(frameData& output)
{
   // Lock frameCount number, get frame count
   rgb_frameNumLock.lock();
   int frame = rgb_frameNum;

   // Check that frame numbers do not match.
   if (output.frameNum == frame)
   {
      rgb_frameNumLock.unlock();
      return -1;
   }

   // Get id of buffer location to capture frame from.
   int id = frame%MAX_FRAMES;

   // Lock readCount-- if 0, grab lock to buffer location, else,
   // just increment readCount.
   rgb_readCountLock[id].lock();
   if (rgb_readCount[id] == 0)
   {
      rgb_readLock[id].lock();
      rgb_readCount[id] = 1;
   }
   else
   {
      ++rgb_readCount[id];
   }

   // unlcok readCount and frameNumLock
   rgb_readCountLock[id].unlock();
   rgb_frameNumLock.unlock();

   // Copy Frame
   cv::cvtColor(*rgb_frames[id].data, *output.data, CV_RGB2BGR);
   output.frameNum = frame;

   // Decrement readCount, unlock frame if last reader.
   rgb_readCountLock[id].lock();
   if (rgb_readCount[id] == 1)
   {
      rgb_readLock[id].unlock();
      rgb_readCount[id] = 0;
   }
   else
   {
      --rgb_readCount[id];
   }
   rgb_readCountLock[id].unlock();
   return 0;
}

bool KinectOpenCVDevice::getDepth(depthFrame16Bit& output)
{
   // Lock frameCount number, get frame count
   depth_frameNumLock.lock();
   int frame = depth_frameNum;
   // Check that frame numbers do not match.
   if (output.frameNum == frame)
   {
      depth_frameNumLock.unlock();
      return -1;
   }

   // Get id of buffer location to capture frame from.
   int id = frame%MAX_FRAMES;

   // Lock readCount-- if 0, grab lock to buffer location, else,
   // just increment readCount.
   depth_readCountLock[id].lock();
   if (depth_readCount[id] == 0)
   {
      depth_readLock[id].lock();
      depth_readCount[id] = 1;
   }
   else
   {
      ++depth_readCount[id];
   }

   // unlcok readCount and frameNumLock
   depth_readCountLock[id].unlock();
   depth_frameNumLock.unlock();

   // Copy Frame
   depth_frames[id].data->copyTo(*output.data);
   output.frameNum = frame;

   // Decrement readCount, unlock frame if last reader.
   depth_readCountLock[id].lock();
   if (depth_readCount[id] == 1)
   {
      depth_readLock[id].unlock();
      depth_readCount[id] = 0;
   }
   else
   {
      --depth_readCount[id];
   }
   depth_readCountLock[id].unlock();
   return 0;
}

void KinectOpenCVDevice::resetCounts()
{
   rgb_frameNumLock.lock();
   depth_frameNumLock.lock();
   rgb_frameNum = 1;
   depth_frameNum = 1;
   rgb_frameNumLock.unlock();
   depth_frameNumLock.unlock();

}
```

<u>kinectapi.cpp</u>

```
#include "kinectapi.h"
//static int blah = 123;
static Freenect::Freenect freenect;
static KinectOpenCVDevice& device = freenect.createDevice<KinectOpenCVDevice>(0);

kinectinterface::kinectinterface()
{
   device.startVideo();
   device.startDepth();
   sleep(1);
   device.resetCounts();
   return;
}

kinectinterface::~kinectinterface()
{
   device.stopVideo();
   device.stopDepth();
   return;
}

Mat* kinectinterface::get8BitRGB()
{
   device.getVideo(rgb);
   lastTimestamp = rgb.timestamp;
   lastFrameNum = rgb.frameNum;
   return rgb.data;
}

Mat* kinectinterface::get16BitDepth()
{
   device.getDepth(depth16);
   lastTimestamp = depth16.timestamp;
   lastFrameNum = depth16.frameNum;
   return depth16.data;
}

Mat* kinectinterface::get8BitDepth()
{
   device.getDepth(depth16Temp);
   if (depth16Temp.frameNum != depth8.frameNum)
   {
      depth16Temp.data->convertTo(*depth8.data, CV_8UC1, 255.0/2048.0);
      depth8.timestamp = depth16Temp.timestamp;
      depth8.frameNum = depth16Temp.frameNum;
   }
   lastTimestamp = depth8.timestamp;
   lastFrameNum = depth8.frameNum;
   return depth8.data;
}

Mat* kinectinterface::get8BitGrayscale()
{
   device.getVideo(rgbTemp);
   if (rgbTemp.frameNum != grayscale.frameNum)
   {
      cvtColor( *rgbTemp.data, *grayscale.data, CV_RGB2GRAY );
      grayscale.frameNum = rgbTemp.frameNum;
      grayscale.timestamp = rgbTemp.timestamp;
   }
   lastTimestamp = grayscale.timestamp;
   lastFrameNum = grayscale.frameNum;
   return grayscale.data;
}

Mat* kinectinterface::get16BitGrayscale()
{
   device.getVideo(rgbTemp);
   if (rgbTemp.frameNum != grayscale16.frameNum)
   {
      cvtColor( *rgbTemp.data, *grayscale16.data, CV_RGB2GRAY );
      grayscale16.frameNum = rgbTemp.frameNum;
      grayscale16.timestamp = rgbTemp.timestamp;
   }
   lastTimestamp = grayscale16.timestamp;
   lastFrameNum = grayscale16.frameNum;

   return grayscale16.data;
}
```

Appendix D Works Cited

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