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COMPARING AND IMPROVING FACIAL RECOGNITION METHOD

Brandon Luis Sierra

California State University – San Bernardino

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COMPARING AND IMPROVING FACIAL RECOGNITION METHOD

A Project
Presented to the
Faculty of
California State University,
San Bernardino

In Partial Fulfillment
of the Requirements for the Degree
Master of Science
in
Computer Science

by
Brandon Luis Sierra
September 2017

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Approved by:

Dr. Haiyan Qiao, Adviser, Computer Science

Dr. Ernesto Gomez, Committee Member

Dr. David Turner, Committee Member

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ABSTRACT

Facial recognition is the process in which a sample face can be correctly identified by a machine amongst a group of different faces. With the never-ending need for improvement in the fields of security, surveillance, and identification, facial recognition is becoming increasingly important. Considering this importance, it is imperative that the correct faces are recognized and the error rate is as minimal as possible. Despite the wide variety of current methods for facial recognition, there is no clear cut best method. This project reviews and examines three different methods for facial recognition: Eigenfaces, Fisherfaces, and Local Binary Patterns to determine which method has the highest accuracy of prediction rate. The three methods are reviewed and then compared via experiments. OpenCV, CMake, and Visual Studios were used as tools to conduct experiments. Analysis were conducted to identify which method has the highest accuracy of prediction rate with various experimental factors. By feeding a number of sample images of different people which serve as experimental subjects. The machine is first trained to generate features for each person among the testing subjects. Then, a new image was tested against the “learned” data and be labeled as one of the subjects. With experimental data analysis, the Eigenfaces method was determined to have the highest prediction rate of the three algorithms tested. The Local Binary Pattern Histogram (LBP) was found to have the lowest prediction rate. Finally, LBP was selected for the algorithm improvement. In this project, LBP was improved by identifying the most

significant regions of the histograms for each person in training time. The weights of each region are assigned depending on the gray scale contrast. At recognition time, given a new face, different weights are assigned to different regions to increase prediction rate and also speed up the real time recognition. The experimental results confirmed the performance improvement.

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CHAPTER ONE

INTRODUCTION

The purpose of this project is to review, compare, and improve face recognition algorithms. Facial recognition is different than facial detection, and in certain situations, can be much more important than facial detection. Facial detection is the ability for a machine to detect whether a face exists in a live test. It answers the yes/no question “is this a face” or “is there a face in the image”. Facial recognition is the ability for a machine to correctly label a face among a group different faces. It answers the question “whose face”. Face recognition is important with regard to biometrics authentication. For security purposes, it is very important to correctly identify a person when attempting to authenticate. This can be necessary for door/area access, airport security and home security. In these situations, it can be imperative that the user presented is correctly identified and either granted access correctly or incorrectly. There are currently multiple applications available on both Android and iPhone that use facial recognition for both phone and application access as a means of additional security in the event that someone that is not authorized has access to another individual’s phone.

CHAPTER TWO

BACKGROUND REVIEW

Overview of Machine Learning and Object Recognition

“Machine learning refers to the study of algorithms that analyze data in order to help computer systems become more accurate over time when completing a task.” [1]. The goal of machine learning is for computer systems to continually improve on the required task, or “learn” how to better complete a required task. This task is done by creating algorithms that the machines use to learn automatically. One example of machine learning could be spam filtering, where the software continually learns what the user considers spam and what is not. Machine learning is used in object recognition to help computer systems to better identify and recognize objects. Object recognition is the computer system’s ability to not only detect that an object exists in an image, but also to identify what the object is. One example of object recognition is facial recognition.

Overview of Facial Recognition

Facial recognition is a technique that is quickly becoming a major goal of machine learning. Recently, with the aid of new algorithms, the ever increasing hardware capabilities, and the constant decrease in price for these advancements, facial recognition is becoming a more heavily researched field.

One of the main reasons for the current expansion of research in this field is that facial recognition aids in security and surveillance. Other applications of facial recognition include: general identity verification, criminal justice systems, image database investigations, “Smart Card” applications, multi-media environments with adaptive human-computer interfaces, video indexing, and witness face reconstruction. These are listed in details below according to [2]:

- Security (access control to buildings, airports/seaports, ATM machines and border checkpoints; computer/ network security; email authentication on multimedia workstations).
- Surveillance (a large number of CCTVs can be monitored to look for known criminals, drug offenders, etc. and authorities can be notified when one is located; for example, this procedure was used at the Super Bowl 2001 game at Tampa, Florida; in another instance, according to a CNN report, two cameras linked to state and national databases of sex offenders, missing children and alleged abductors have been installed recently at Royal Palm Middle School in Phoenix, Arizona).
- General identity verification (electoral registration, banking, electronic commerce, identifying newborns, national IDs, passports, drivers’ licenses, employee IDs).
- Criminal justice systems (mug-shot/booking systems, post-event analysis, forensics).

- Image database investigations (searching image databases of licensed drivers, benefit recipients, missing children, immigrants and police bookings).
- “Smart Card” applications (in lieu of maintaining a database of facial images, the face-print can be stored in a smart card, bar code or magnetic stripe, authentication of which is performed by matching the live image and the stored template).
- Multi-media environments with adaptive human computer interfaces (part of ubiquitous or contextaware systems, behavior monitoring at childcare or old people’s centers, recognizing a customer and assessing his needs).
- Video indexing (labeling faces in video).
- Witness face reconstruction.

There are also two main categories involved in facial recognition and identification. These are face verification and face identification. Although they seem similar, there is a difference between the two. According to [3], “Face verification is a 1:1 match that compares a face image against a template face images, whose identity is being claimed. On the contrary, face identification is a 1:N problem that compares a query face image against all image templates in a face database to determine the identity of the query face.” Currently, there are applications on the market for facial recognition. Most of these applications would use facial recognition as a means for facial verification. When facial

verification is used for device security, there needs to be a 1:1 match. A device will only grant access if there is match between who should be allowed, and who is being recognized. An example of such an application is Windows Hello, which is included in Windows 10. One of the key points to consider before any face can be recognized is a good object classifier must first be developed. To develop a strong object classifier, a number of sample data must be preloaded into the machine in order for the machine to learn what the face should look like. The machine takes this sample data and, depending on the algorithm, develops discriminative features to look for in objects presented to it.

Challenges in Object Recognition

A robot can be any computer that is capable of machine learning. There are a number of challenges that arise when a robot tries to learn new information. One such issue is developing a strong classifier. A weak classifier occurs when the robot has an error rate that is greater than 50% over any distribution. In order to develop a strong classifier, there must be a large enough training set of labeled sample images for the robot to develop what discriminative features to look for. If the training data is not large enough, the machine may develop false positives. False positives are objects that are detected by the robot that should not be. For example, given a robot that has been designed to detect a human face and given an image of trees, the machine will falsely detect a human face in

the image of trees. However, the training data must not be too large, so as to avoid a low detection rate. A dataset range is determined through trial and error, depending on the number of features in an image. If the robot has been taught to detect too many discriminative features, it might not be able to detect an image with some, but not most of, these features. For example, given a robot that has been designed to detect a human face and was given more images to learn from containing faces having either short hair, no glasses, or earrings, the robot might not be able to detect the same face having long hair, glasses, or no earrings. These factors are especially important in facial identification. Another issue that can lead to false detections, especially in facial identification, is using training data of subjects who look too similar. For example, if training data consists of multiple family members who share similar facial features, the robot may have a difficult time correctly identifying one subject over the other. This could mean a low identification rate between parent/child, siblings, or even cousins whose facial features are similar enough. Other factors also exist that can pose challenges to recognizing a face. According to [3] five factors that can play an important role in face recognition are:

- *Illumination* variations due to skin reflectance properties and due to the internal camera control. Several 2D methods do well in recognition tasks only under moderate illumination variation, while performances noticeably drop when both illumination and pose changes occur.

- *Pose* changes affect the authentication process, because they introduce projective deformations and self-occlusion. Even if methods dealing with up to 32 head rotation exists, they do not solve the problem considering that security cameras can create viewing angles that are outside of this range when positioned. On the contrary, with exception of extreme expressions such as scream, the algorithms are relatively robust to *facial expression*.
- Another important factor is the *time delay*, because the face changes over time, in a nonlinear way over long periods. In general, this problem is harder to solve with respect to the others and not much has been done especially for age variations.
- At last, *occlusions* can dramatically affect face recognition performances, in particular if they located on the upper-side of the face, as documented in literature.

Current Work Review

Currently, facial recognition is a heavily researched field, with researchers studying numerous different algorithms. Figure 1 shows some of the different methods that are being tested [3]. Some popular methods are: Eigenfaces, Fisherfaces, and Local Binary Pattern Histogram. Many of the listed methods can use sample training data that has been compiled into databases by large research organizations (see Figure 2) [3]. One project, OpenCV, currently uses

the Eigenfaces, Fisherfaces, and Local Binary Pattern Histogram algorithms to do facial recognition. These same algorithms codes were used to test, compare, and improve on the Local Binary Pattern Histogram in this project.

Method		Databases	Image size	Max[G]-Max[P]	Time lapse	Recog. rate (%)	Expr.	Ill.	Pose	Occl.	Age
Authors	Name										
Martínez and Kak (2001)	PCA	AR-Faces	85 × 60	100–250	No	70		No	No	No	No
Martínez and Kak (2001)	LDA	AR-Faces	85 × 60	100–250	No	88		No	No	No	No
Belhumeur et al. (1997)	Fisherfaces	YALE		144–16	No	99.6	Yes	Yes	No	No	No
Yu and Yang (2001)	Direct LDA	ORL	112 × 92	200–200	No	90.8	Yes	Yes	Yes	No	No
Lu et al. (2003)	DF-LDA	ORL	112 × 92	200–200	Yes	96		Yes	No	No	No
		UMIST	112 × 92	160–415	No	98		No	No	No	No
Cevikalp et al. (2005)	DCV	Yale	126 × 152	15–150	No	97.33		Yes	No	No	No
		AR-Faces	229 × 299	350–350	Yes	99.35					
Bartlett Marian et al. (2002)	ICA	FERET	60 × 50	425–421	Yes	89	Yes	No	No	No	No
Lin et al. (1997)	PDBNN	SCR	80 × 20	320–1280	No	100	Yes	Yes	Yes	No	No
		FERET		200–200	No	99	Yes	Yes	No	No	No
		ORL			No	96		Yes	Yes	No	No
Joo Er et al. Meng et al. (2002)	RBF	? ORL PropertyDB	160 × 120	300–300		98.1 100	Yes		Yes	No	No
Perronnin and Dugelay (2003)	HMM	FERET	128 × 128	500–500	No	97	Yes	No	No	No	No
Lades et al. (1993)	DLA	PropertyDB	128 × 128	88–88	No	90.3	Yes		Yes	No	No
Liu (2004)	Gabor EFM	FERET	128 × 128	200–100	No	99	Yes	No	No	No	No
		ORL	128 × 128	200–200	No	100	Yes	No	Yes	No	No
Wiskott et al. (1997)	EGM	FERET	256 × 384	250–250	No	80	Yes		Yes	No	No
		PropertyDB		108–//		90	Yes		Yes	No	No
Garcia et al. (2000)	WPA	MIT	480 × 640	155–155		80.5	Yes	Yes		No	no
		FERET	256 × 384	200–400		89					
Kouzani et al. (1997)	IFS	PropertyDB	64 × 64	100–100		100		No	No	No	No
Tan and Tan (1999)	IFS	ORL	92 × 112	200–//	No	95				No	No
Ebrahimpour-Komleh et al. (2001)	IFS	MIT	480 × 640	90–90		90			Yes	No	No
Chen et al. (2003)	Th-Infrared	PropertyDB		166–166	No	98	Yes	Yes	No	No	No
Socolinsky and Selinger (2004b)	Thermal	PropertyDB	99 × 132	770–2310	Yes	93	Yes	Yes	No	No	No
Buddharaju et al. (2004)	Th-Spectrum	Equinox		225–2500		86.8	Yes		Yes	No	No
Pan et al. (2003)	Hyperspectral	PropertyDB		200–1200	Yes	92	No	Yes	No	No	No
<i>Open question methods</i>											
Gao and Leung (2002)	LEM	Bern		40–160	No	72.09	Yes		Yes	No	No
		AR-Faces		112–336		86.03		Yes	No	No	No
		Yale		15–150		85.45		Yes	No	No	No
Kim et al. (2003)	ICA	Subset of AR Faces, Yale, ORL, Bern and FERET	46 × 56	1685–1490		98		Yes	Yes	No	No
Li et al. (2004)	LDA/GSVD	CMU_PIE/Pose27		68–1360	No	100	No	Yes	No	No	No
	LDA/QR	YaleB/Pose00		80–432	No	99.53 99 98.03		Yes	No	No	No
Georghiades et al. (2001)	Cones Gen.	Yale B	36 × 42	450–4050	No	97	No	Yes	Yes	No	No
Okada and von der Malsburg (2002)	Linear Subspaces	ATR-Database		2821–804	No	98.7	n	No	Yes	No	No
Gross et al. (2002)	Eigen Lights	CMU-PIE		5304–5304	No	36	No	Yes	Yes	No	No

Figure 1. Facial Recognition Algorithms [3]

Name	RGB/ gray	Image size	Number of people	Pictures/ person	Number of conditions	Available	Web address
AR Face Database*	RGB	576 × 768	126 70 Male 56 Female	26	i, e, o, t	Yes	http://rv11.ecn.purdue.edu/~aleix/aleix_face_DB.html
Richard's MIT database	RGB	480 × 640	154 82 Male 74 Female	6	p, o	Yes	
CVL Database	RGB	640 × 480	114 108 Male 6 Female	7	p, e	Yes	http://www.lrv.fri.uni-lj.si/facedb.html
The Yale Face Database B*	Gray Scale	640 × 480	10	576	p, i	Yes	http://cvc.yale.edu/projects/yalefacesB/yalefacesB.html
The Yale Face Database*	Gray Scale	320 × 243	15 14 Male 1 Female	11	i, e	Yes	http://cvc.yale.edu/projects/yalefaces/yalefaces.html
PIE Database*	RGB	640 × 486	68	~608	p, i, e	Yes	http://www.ri.cmu.edu/projects/project_418.html
The UMIST Face Database	Gray	220 × 220	20	19–36	p	Yes	http://images.ee.umist.ac.uk/danny/database.html
Olivetti Att – ORL*	Gray	92 × 112	40	10		Yes	http://www.uk.research.att.com/facedatabase.html
(JAFFE) Database	Gray	256 × 256	10	7	e	Yes	http://www.mis.atri.co.jp/~mlyons/jaffe.html
The Human Scan Database	Gray	384 × 286	23	~66		Yes	http://www.humanscan.de/support/downloads/facedb.php
The University of Oulu Physics-Based Face Database	Gray	428 × 569	125	16	i	Cost \$50	http://www.ee.oulu.fi/research/imag/color/pbfd.html
XM2VTSDB	RGB	576 × 720	295		p	Frontal \$153 Side \$229.5	http://www.ee.surrey.ac.uk/Research/VSSP/xm2vtsdb/
FERET*	Gray RGB	256 × 384	30,000		p, i, e, i/o, t	Yes	http://www.itl.nist.gov/iad/humanid/feret/

The "*" points out most used databases. Image variations are indicated by (i) illumination, (p) pose, (e) expression, (o) occlusion, (i/o) indoor/outdoor conditions and (t) time delay.

Figure 2. Training Set Databases [3]

CHAPTER THREE

METHODOLOGY

The three methods that were used and compared in this project were: Eigenfaces, Fisherfaces, and Local Binary Patterns Histograms. The three methods were compared by using the OpenCV project, collecting a number of photos (in the range of 20-50 per training person,) uploading images to the program for training, and then comparing the accuracy of each method to see if it could correctly identify a live video of some of the trained subjects.

Eigenfaces

To generate a set of Eigenfaces, principal component analysis (PCA) must be applied on a set of images of different human faces. This is done to “identify vectors which best account for the distribution of face images within” the image space [4]. First, a sample set of facial images must be gathered. It is ideal to use sample data with similar lighting and have the faces in similar poses with the eyes and mouths aligned across the images. The next step is to compute and subtract the mean. Following this step, the covariance matrix is calculated. Next, the eigenvectors and eigenvalues will be calculated from the covariance matrix. The eigenvectors all have the same dimensionality as the original images and are therefore also considered an image. Thus these are

called Eigenfaces. The eigenvectors are then ordered in descending order by their eigenvalues. The Eigenfaces with the largest eigenvalue are kept.

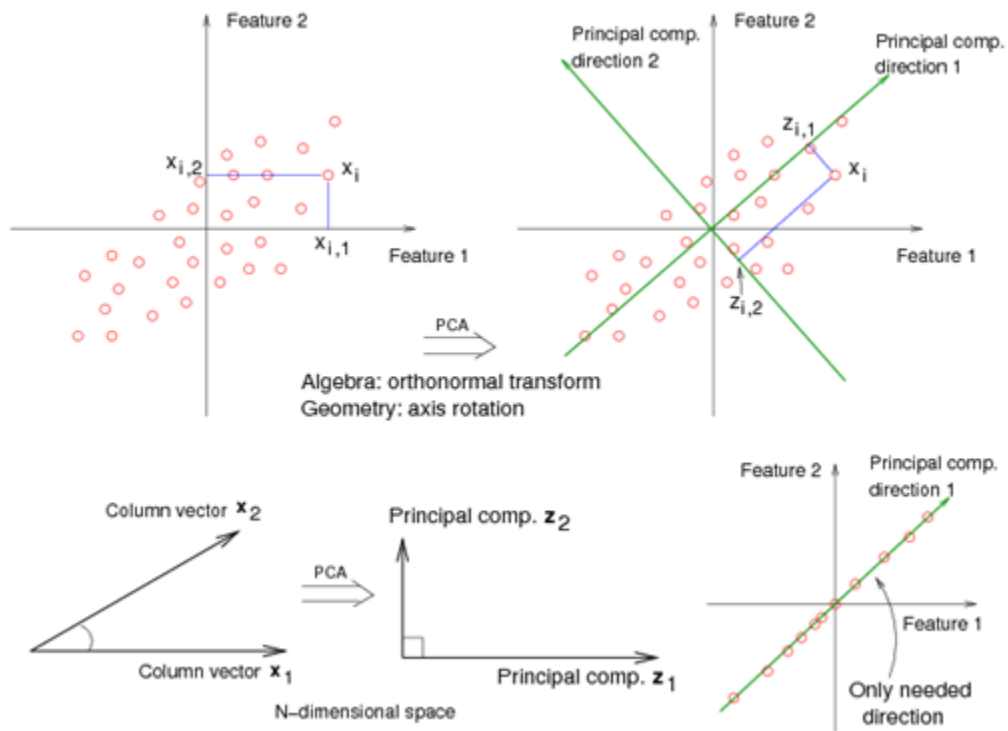


Figure 3. Principal Component Analysis Dimensionality Reduction

<https://onlinecourses.science.psu.edu/stat857/node/35>

Fisherfaces

The Fisherface method is similar the Eigenface method, but instead uses a technique called Fisher's linear discriminant (FLD) analysis along with PCA. PCA is used to reduce the dimensionality from $N - c$, and then FLD to further

reduce the dimensionality to $c - 1$, where N is the number of images in the training data and c is the number of classes. Because the Eigenface method does not take into consideration classes, some discriminative data could possibly be lost when discarding data during the reduction. The advantage to Fisherfaces is that it is less sensitive to differences in lighting and the positions of the faces in the sample data compared to Eigenfaces method. After sample data is gathered, the scatter matrices are calculated. This method maximizes the ratio of between-class scatter and within-class scatter. Figure 5 shows the difference in dimensionality reduction using both PCA and FLD with two classes. Note that using PCA, both class 1 and class 2 are not kept separate, as is the case when using FLD. This demonstrates the maximization of the ratio of class scatter.

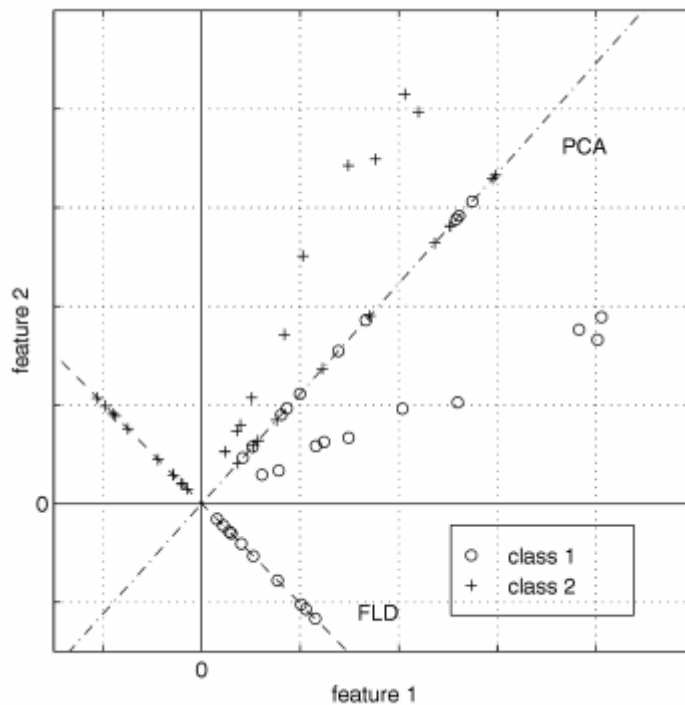


Figure 4. Principle Component Analysis and Fisher Linear Discriminant

<https://onlinecourses.science.psu.edu/stat857/node/35>

Local Binary Patterns Histograms

The Local Binary Patterns (LBPH) method compares the histogram of a displayed image and compares it to the original sample input images. This particular method examines a provided image by dividing the image into smaller regions to generate binary patterns for each pixel. It then graphs the binary patterns to a single feature histogram by comparing the neighbors of each pixel. A gray value is assigned to the center pixel as well as to each neighbor pixel. If the gray scale value of each neighbor is greater than or equal the center pixel's

gray scale value, then a '1' value is assigned to the neighbor pixel. If the value is less, a '0' value is assigned. The binary pattern is generated by starting with the top left pixel's binary value, and appending each additional binary value of each pixel by moving in a clockwise pattern. This binary value is then converted to a decimal value. This is repeated for every pixel and a histogram is eventually generated for this region. This process is done for every region, and then the histograms for each region are concatenated into one large histogram.

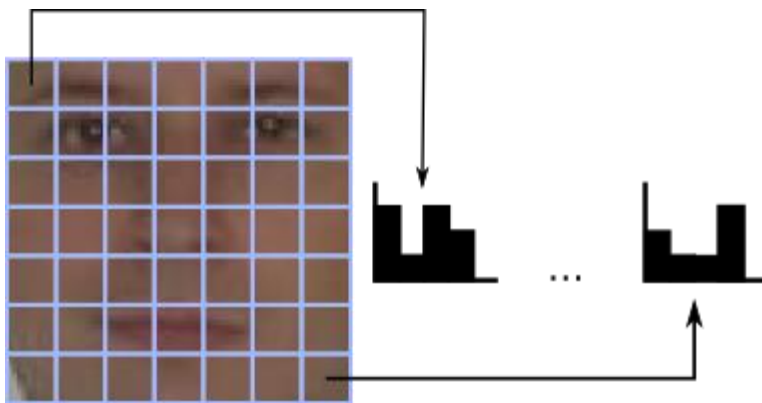


Figure 5. Spatial Histograms http://bytefish.de/blog/local_binary_patterns/

When an image is presented to predict if the image is known to the machine, it uses the same technique and compares the distances of the two histograms to see if the images are similar. The advantage to this method, as written by, is that several studies have demonstrated that using this method provides consistently accurate results for face recognition, both in terms of speed

and discrimination performance [5]. This method also seems to be strong for facial images with varying facial expressions, lighting conditions, image rotation and aging persons. The Local Binary Pattern Histogram has evolved to now contain two different methods, an “original” and an “extended.”

Original Local Binary Patterns Histogram

The Original Local Binary Pattern (olbp) Histogram uses eight neighbors and uses a radius of one. That means that every pixel is compared with each of the eight neighbor pixels that touch it. The one disadvantage to this method is that its computational time can be large, depending on the number of pixels in an image. For example, an image with a size of 200 x 200 pixels will have 40,000 pixels that will need to be compared with eight neighbors.

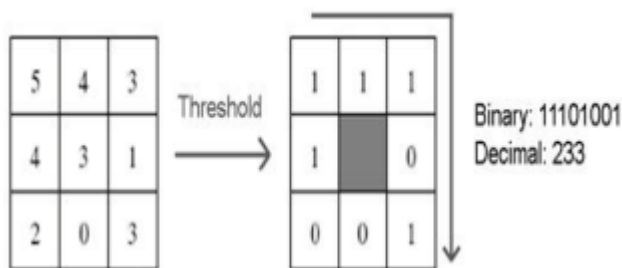


Figure 6. Binary Values from Neighbors Comparison [5]

Below is the OpenCV code for calculating the binary values of eight neighbors depending on the gray scale value.

```

for(int i=1;i<src.rows-1;i++) {
    for(int j=1;j<src.cols-1;j++) {
        _Tp center = src.at<_Tp>(i,j);
        unsigned char code = 0;
        code |= (src.at<_Tp>(i-1,j-1) >= center) << 7;
        code |= (src.at<_Tp>(i-1,j) >= center) << 6;
        code |= (src.at<_Tp>(i-1,j+1) >= center) << 5;
        code |= (src.at<_Tp>(i,j+1) >= center) << 4;
        code |= (src.at<_Tp>(i+1,j+1) >= center) << 3;
        code |= (src.at<_Tp>(i+1,j) >= center) << 2;
        code |= (src.at<_Tp>(i+1,j-1) >= center) << 1;
        code |= (src.at<_Tp>(i,j-1) >= center) << 0;
        dst.at<unsigned char>(i-1,j-1) = code;
    }
}

```

Figure 7. Original Local Binary Pattern Source Code

Extended Local Binary Patterns Histogram

The Extended Local Binary Pattern (elbp) Histogram is a bit different than the original, in that it allows a user to specify the number of neighbors to use as well as the radius.

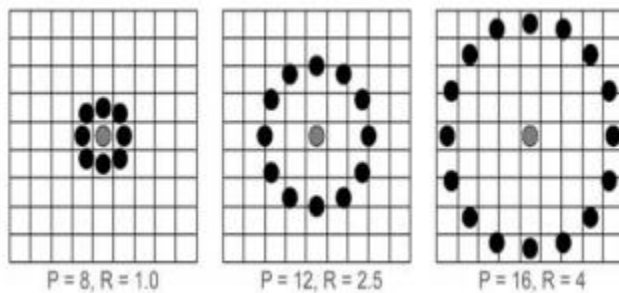


Figure 8. Extended Local Binary Pattern Neighbors Calculation [5]

When the default neighbor count and radius change, a new formula needs to be used to calculate the x and y coordinate of the neighboring pixels. Bilinear interpolation will need to be done in the event that the x and y coordinate of the neighbor's pixels are not in the center of the pixel.

$$LBP_{p,r} = \sum_{n=0}^{p-1} s(x_{r,n} - x_{0,0}) 2^n, \quad s(x) = \begin{cases} 1, & x \geq 0 \\ 0, & x < 0 \end{cases}$$

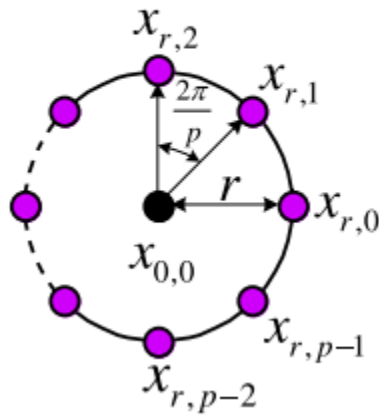


Figure 9. X and Y Coordinates of Extended Local Binary Pattern

<http://www.sciencedirect.com/science/article/pii/S0262885612000066>

The formula is as follows:

Equation 1. Formula for X and Y Coordinates

$$\left(-r \sin\left(\frac{2\pi n}{p}\right), r \cos\left(\frac{2\pi n}{p}\right) \right) \quad (1)$$

where r is radius and p is the number of neighbors.

Below is the OpenCV code for calculating the binary values of a given set of neighbors.

```
for(int n=0; n<neighbors; n++) {
    // sample points
    float x = static_cast<float>(-radius *
sin(2.0*CV_PI*n/static_cast<float>(neighbors)));
    float y = static_cast<float>(radius *
cos(2.0*CV_PI*n/static_cast<float>(neighbors)));
    // relative indices
    int fx = static_cast<int>(floor(x));
    int fy = static_cast<int>(floor(y));
    int cx = static_cast<int>(ceil(x));
    int cy = static_cast<int>(ceil(y));
    // fractional part
    float ty = y - fy;
    float tx = x - fx;
    // set interpolation weights
    float w1 = (1 - tx) * (1 - ty);
    float w2 =      tx  * (1 - ty);
    float w3 = (1 - tx) *      ty;
    float w4 =      tx  *      ty;
    // iterate through your data
    for(int i=radius; i < src.rows-radius;i++) {
        for(int j=radius; j < src.cols-radius;j++) {
            // calculate interpolated value
            float t = static_cast<float>(w1*src.at<_Tp>(i+fy,j+fx) +
w2*src.at<_Tp>(i+fy,j+cx) + w3*src.at<_Tp>(i+cy,j+fx) + w4*src.at<_Tp>(i+cy,j+cx));
            // floating point precision, so check some machine-dependent epsilon
            dst.at<int>(i-radius,j-radius) += ((t > src.at<_Tp>(i,j)) || (std::abs(t-
src.at<_Tp>(i,j)) < std::numeric_limits<float>::epsilon())) << n;
        }
    }
}
```

Figure 10. Extended Local Binary Pattern Source Code

Pros and Cons of Algorithms

Each of the three algorithms mentioned has its own advantages and disadvantages. There are many different algorithms for facial recognition due to no single method being the most optimal in one area, without sacrificing an advantage in another area. Table 1 lists the different pros and cons of the three tested algorithms.

Table 1. Algorithm Pros and Cons

Algorithm	Pros	Cons
Eigenfaces	<ul style="list-style-type: none">-Agnostic to object even being a face-Adequately reduces statistical redundancy in a face image representation	<ul style="list-style-type: none">-Sensitive to light-Sensitive to pose and facial expressions-Sensitive to pixel misalignment
Fisherfaces	<ul style="list-style-type: none">-Achieves greater between-class scatter, thus making classification easier compared to Eigenfaces-Insensitive to light	<ul style="list-style-type: none">-If between-class scatter is large, then within-class scatter could be large
Local Binary Patterns	<ul style="list-style-type: none">-Resistance to lighting changes-Low computational complexity-Ability to code fine details	<ul style="list-style-type: none">-Produce long histograms, which can slow down recognition speed, especially on large training database-Can miss local structure as doesn't

	-One of the best performing texture descriptors	consider effect of center pixel -Small spatial support, in its basic form cannot properly detect large scale textual structures (olb)
--	---	--

Local Binary Patterns Histogram Flowchart

The steps for a generic facial recognition flowchart is described in Figure 10. Every facial recognition algorithm needs a training method to calculate a comparison reference. The training method for the Local Binary Pattern Histogram is described in Figure 11. In the training method for the Local Binary Pattern Histogram algorithm, the two methods that compute the most calculations are the extended local binary pattern (elbp) and spatial_histogram methods. The elbp method calculates the X and Y coordinates of the eight neighbors for each center pixel that will be used to calculate the binary pattern. The binary pattern is then calculated by comparing the gray scale values of the eight neighbors to the center pixel. The binary value is then converted into a decimal number (see Figure 12). The spatial histogram function calculates a histogram for each image. The function first calculates how many regions will be used for the training image. This is determined before run time by manually entering a static value into the code by for a width and height to be used. The size of the region is calculated by dividing the number of pixels of the image by

both the width and height. After the size of each region is calculated, the range of each region must then be determined and the decimal values that were calculated for each pixel in the elbp method are stored in a matrix ordered by region. A histogram for each region is then calculated using the normalized decimal values. All of the regional histograms are then concatenated into one large histogram. These are then stored in a separate matrix (see Figure 13). This is done for each image in the training set and added to a vector that stores the matrix of each image. This completes the training function. The prediction function performs both the elbp and spatial_histogram functions, similar to the training function. The difference is that the information is only calculated on the live video image, rather than on the whole training set. The histogram of the live image is then compared to the histogram of every image of the training set that is stored in the vector. The histograms are compared using the Chi Square Distance method, which can be defined in Equation 2.

Equation 2. Chi Square Distance Formula

$$x_{\omega}^2(x, \varepsilon) = \sum_{j,i} \omega_j \frac{(x_{i,j} - \varepsilon_{i,j})^2}{x_{i,j} + \varepsilon_{i,j}} \quad (2)$$

The distance between the two histograms is stored as variable *dist*. Each distance is compared with the lowest distance (the initial comparison automatically defaults to the least distance). If the new distance is less than the

least distance, the new distance becomes the least distance. If the new distance is greater, no values change and the next image is compared to the live image. After each image in the training set has been compared to the live image, whichever image has the lowest distance is determined to be the prediction result (see Figure 14).

Facial Recognition Flow Chart

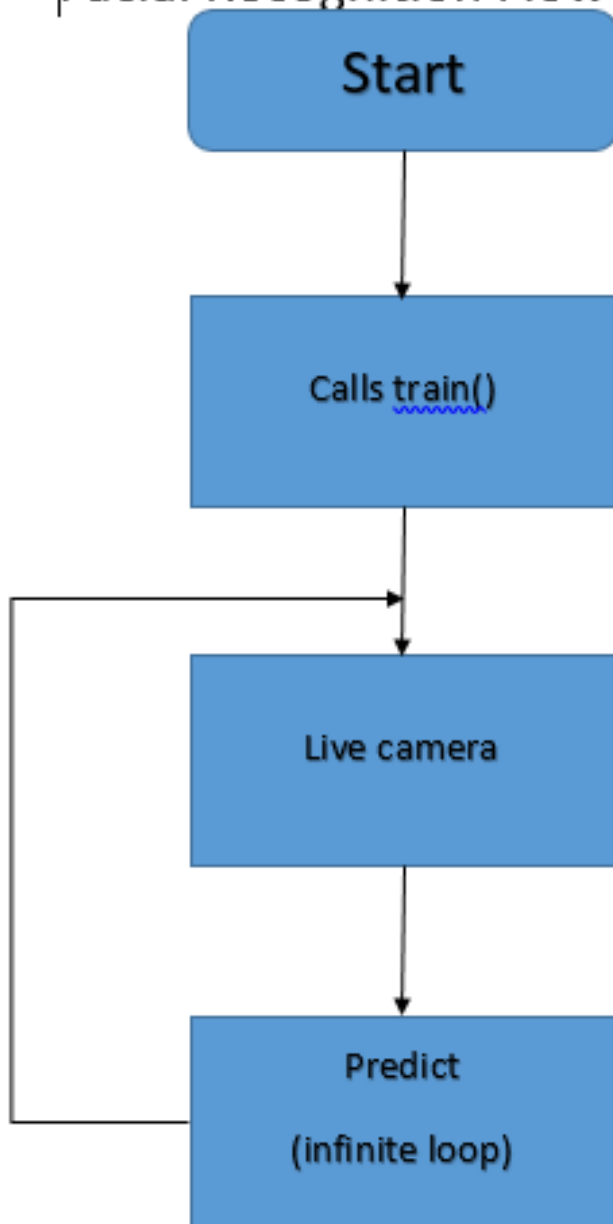


Figure 11. Facial Recognition Flow Chart

LBPH Train Flow Chart

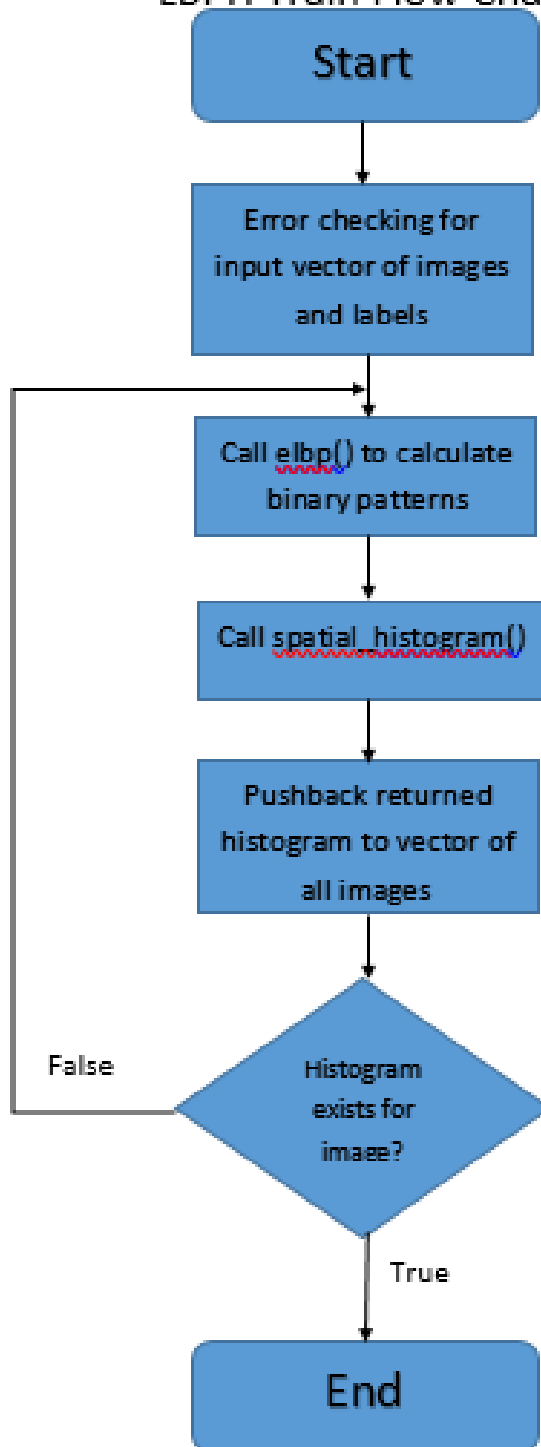


Figure 12. Local Binary Pattern Train Flow Chart

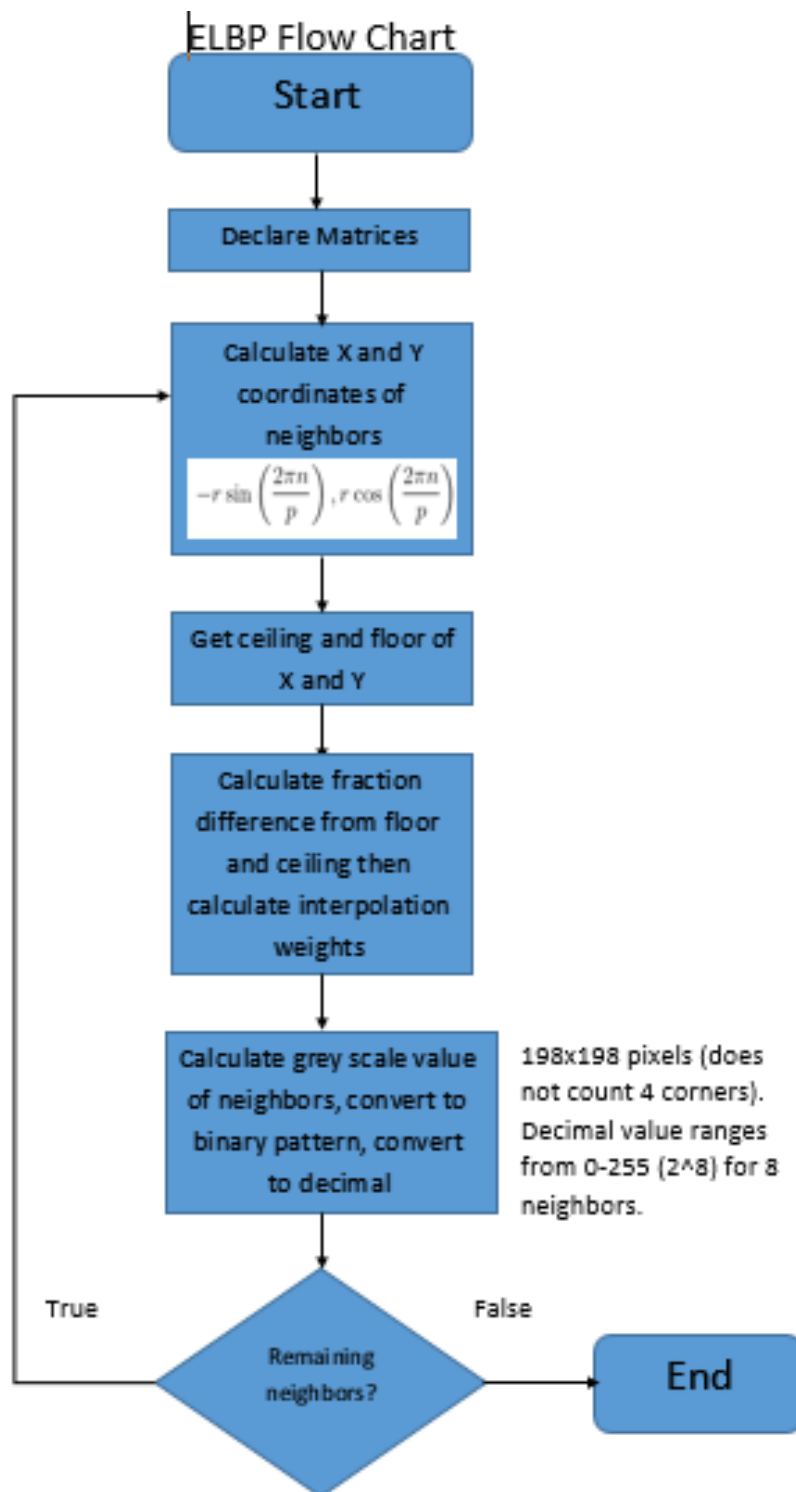


Figure 13. Extended Local Binary Pattern Flow Chart

LBPH Spatial Histogram (Original) Flow Chart

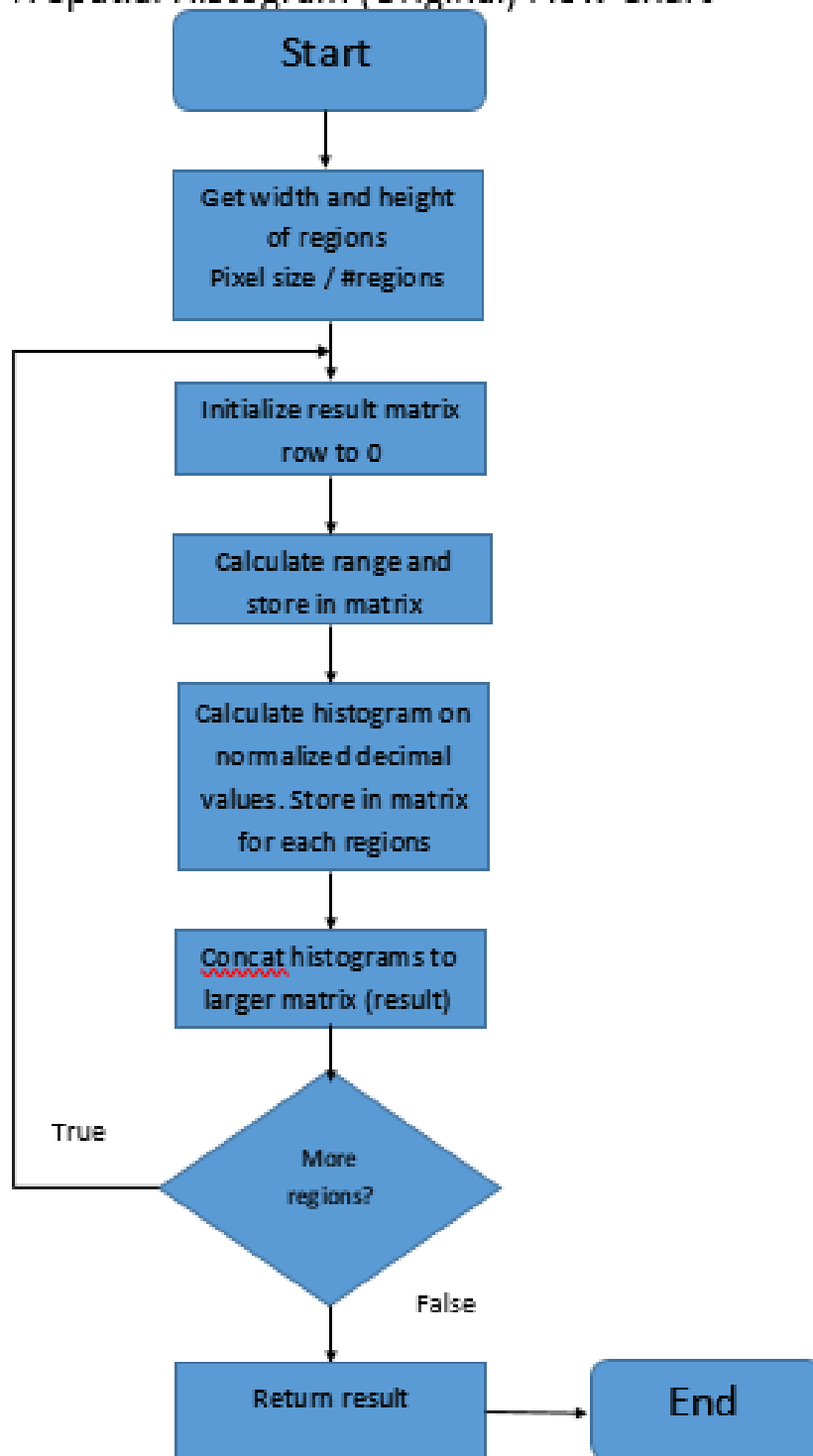
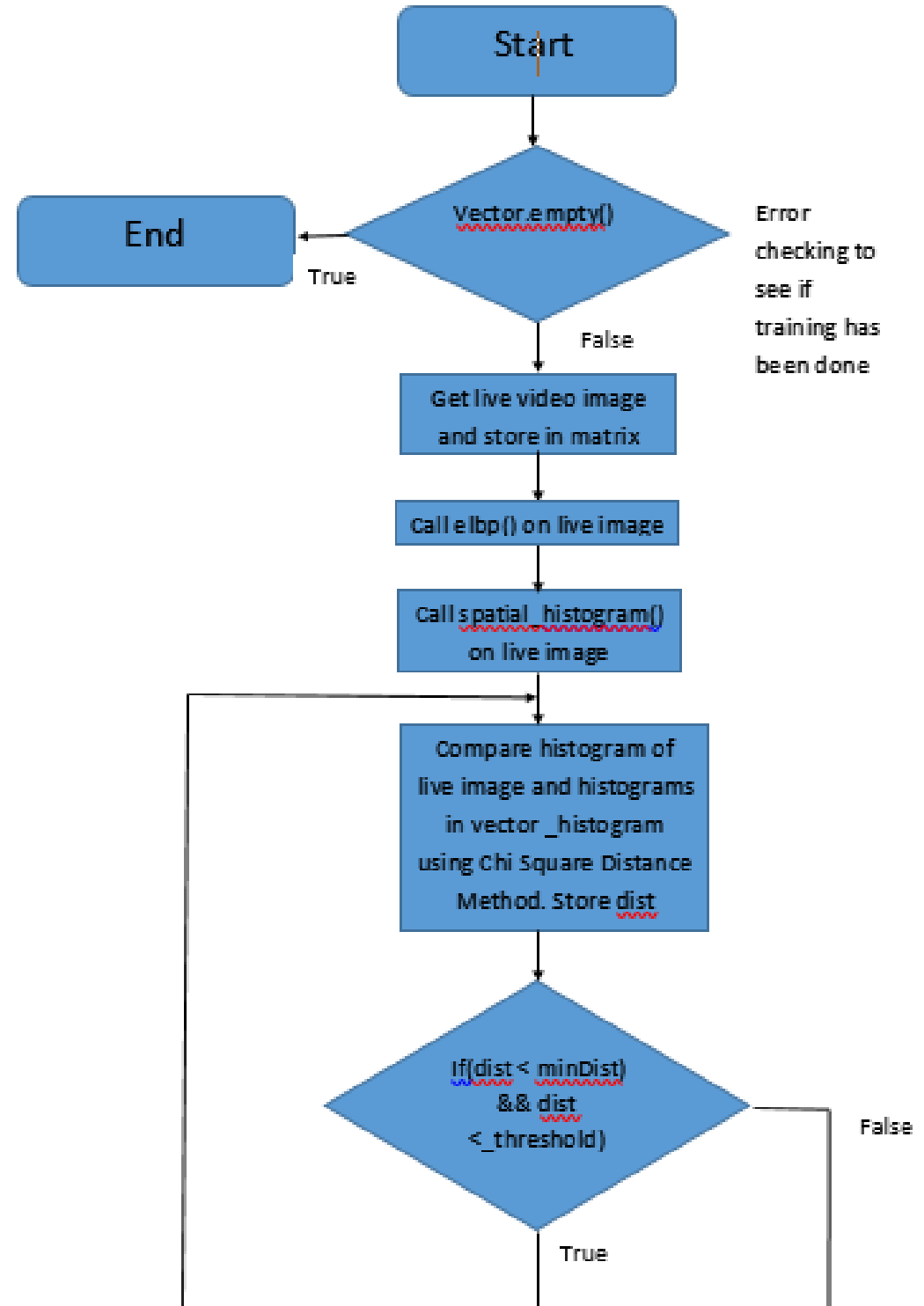


Figure 14. Local Binary Pattern Spatial Histogram (Original) Flow Chart

LBPH Predict Flow Chart



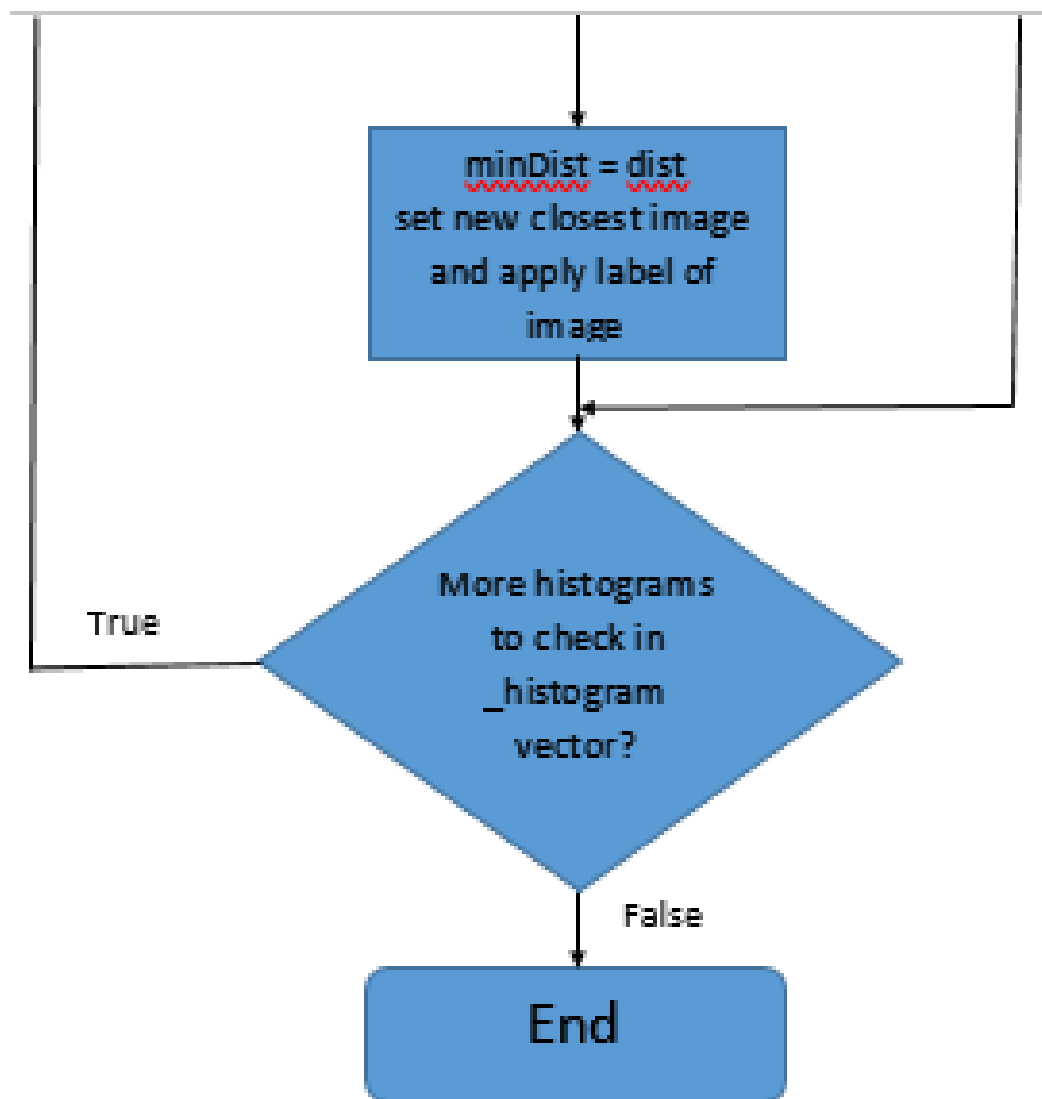


Figure 15. Local Binary Pattern Predict Flow Chart

CHAPTER FOUR

IMPLEMENTATION AND EXPERIMENTAL RESULTS

Downloading OpenCV, CMake, and Visual Studios

Below are the steps to setup the OpenCV projects in Visual Studios:

1. Install a preferred version of Visual Studios to build and compile the project. Note that depending on the version of Visual Studios installed, there may be some necessary changes to building the project with CMake; the reason being that the different versions of Visual Studios (i.e.: 2010, 2012, 2015, etc.) can occasionally use different libraries. The latest trial version can be downloaded from <https://www.visualstudio.com/downloads/>.
2. Obtain the necessary project files by downloading the project from OpenCV which can be found at <http://opencv.org/releases.html>.
3. Download and install CMake to extract and build the OpenCV project. This can be downloaded from the website at <https://cmake.org/download/>.
4. Run CMake to build the OpenCV project. One thing to note is that the **facerec_eigenfaces.cpp**, **facerec_fisherfaces.cpp**, **facerec_lbph.cpp**, **facerec_save_load.cpp**, and **facerec_video.cpp** were not originally in the samples folder for the OpenCV project. If these files are not in the proper location when building the project, the executables will not be generated and will be unable to run. These five files have to copied from

C:\opencv\sources\modules\contrib\doc\facerec\src to

C:\opencv\sources\samples\cpp.

5. Now that these files have been copied to the appropriate location, CMake can be used to generate the project. Below are some screenshots of the different settings that were determined to work best to generate the project. The first step is to open CMake and choose the location of the OpenCV source files and also where the binaries may be saved. Next, click on the “Configure” button. Figures 16-19 shows the settings that were used in this project. Click the “Generate” button. Because Visual Studios 2010 was used in this project, the native environment for VS10 was chosen. This will vary depending on the version of Visual Studios that is installed.

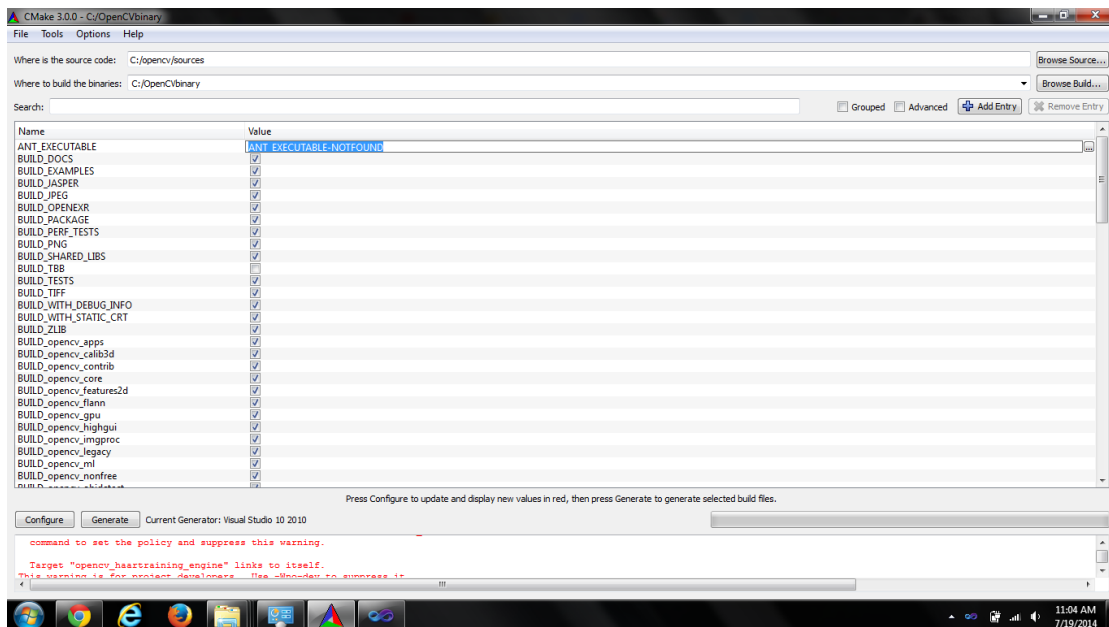


Figure 16. CMake Settings 1

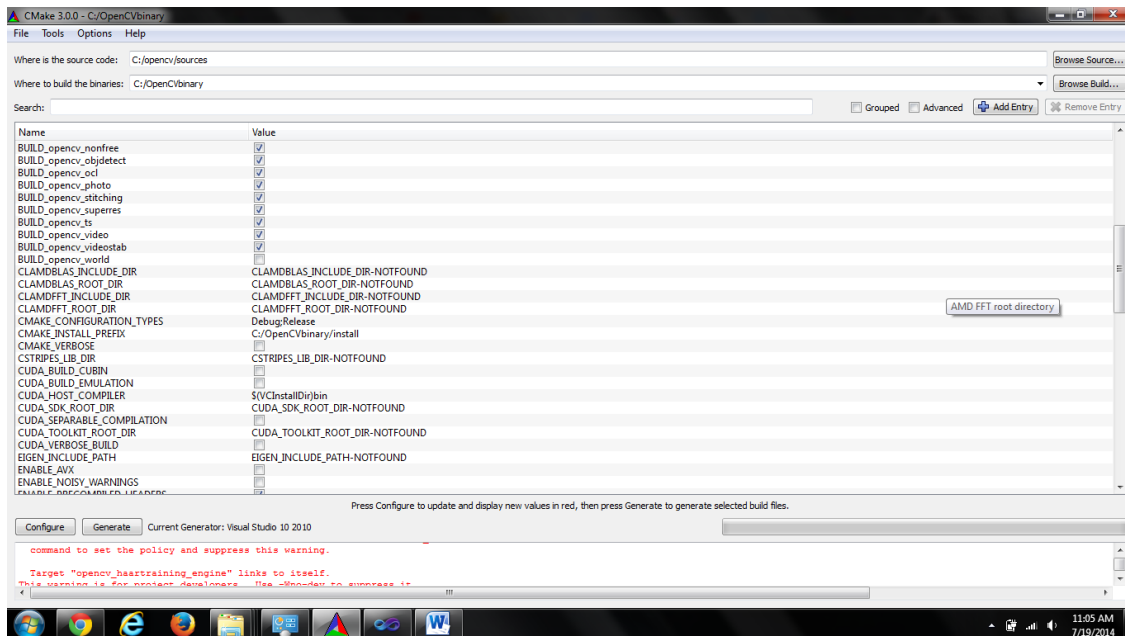


Figure 17. CMake Settings 2

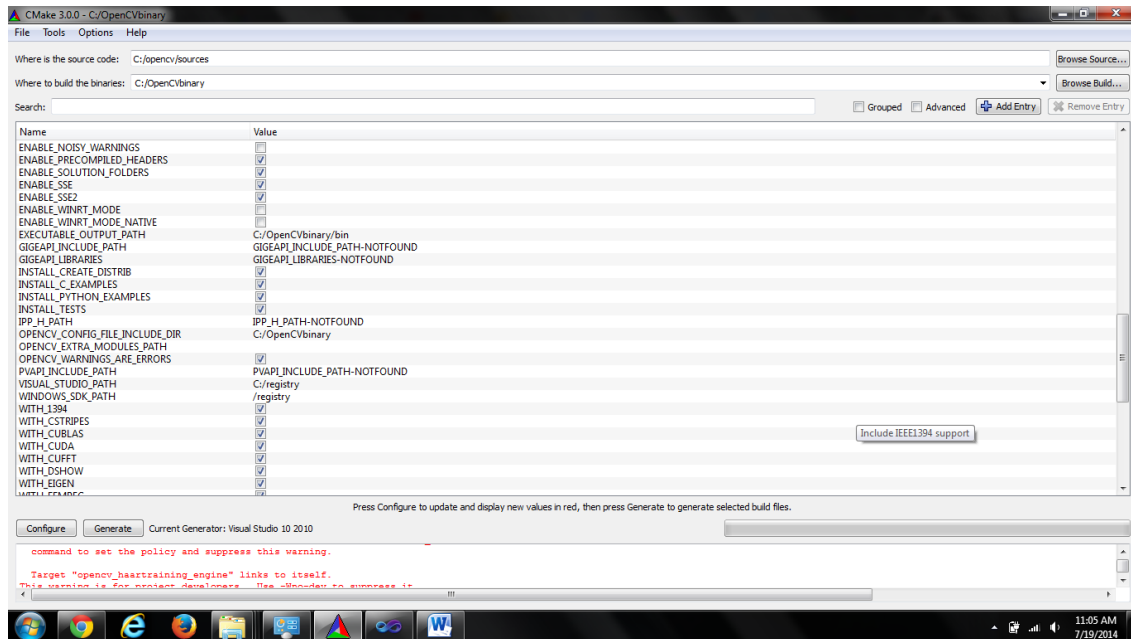


Figure 18. CMake Settings 3

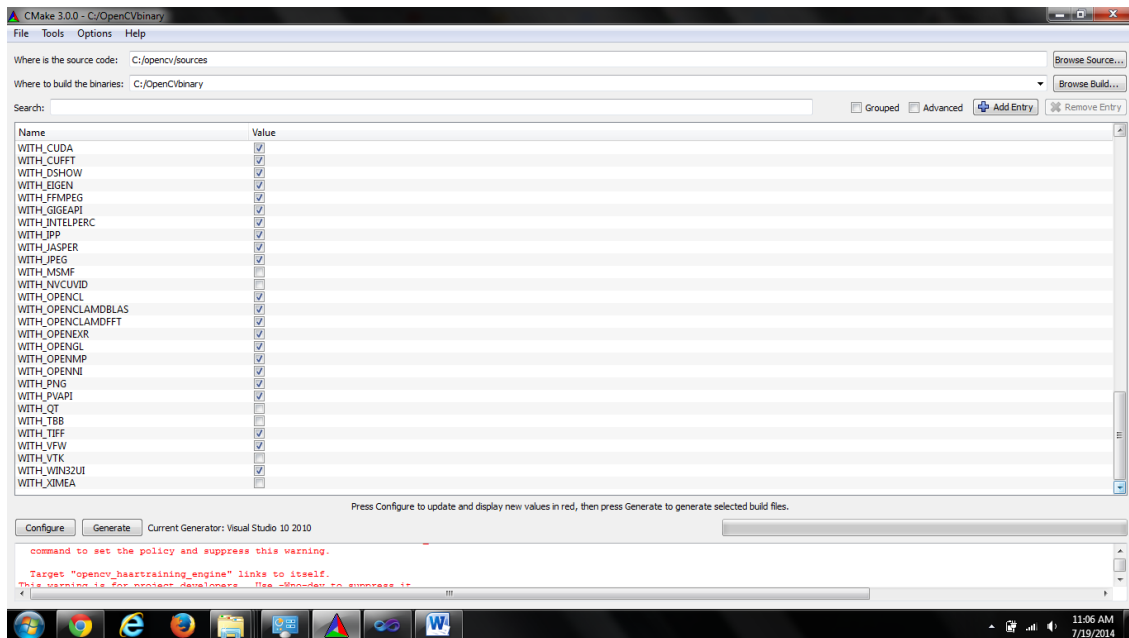


Figure 19. CMake Settings 4

Compiling, Executing, and Testing the Samples

1. **Studios.** By changing “**Treat Warnings As Errors**” to “**No**”, the project was then able to compile easier (see Figures 20-22).

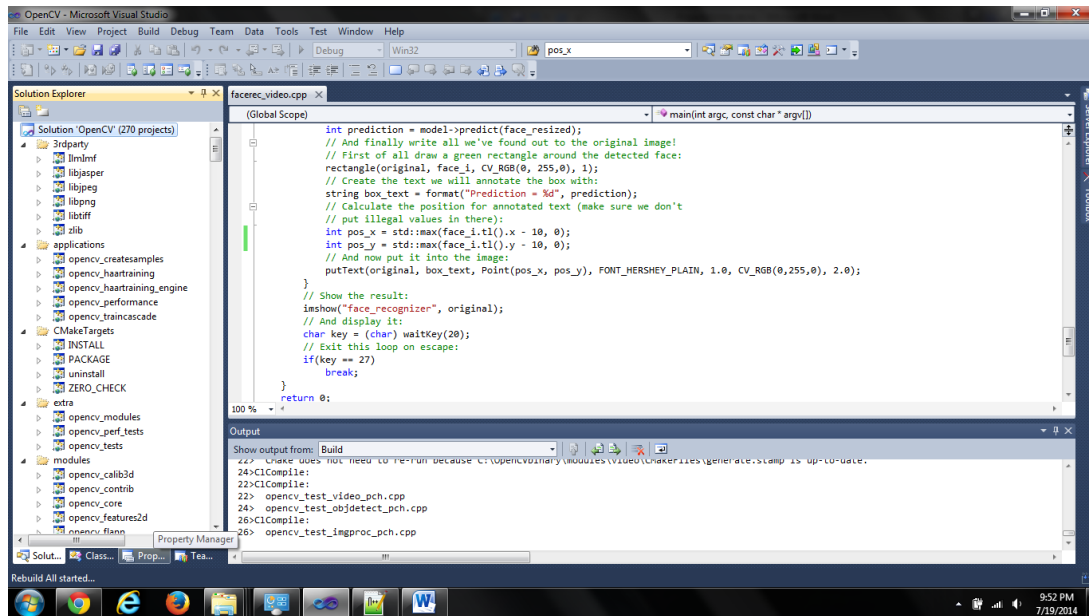


Figure 20. Visual Studios Settings 1

Click on Property Manager tab.

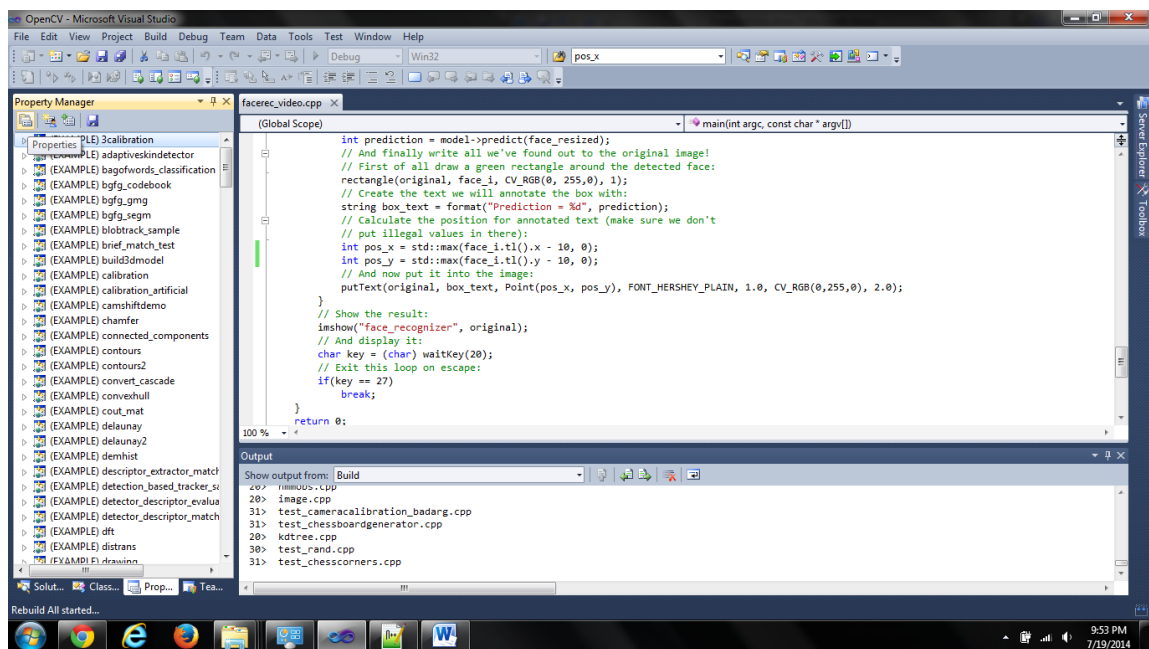


Figure 21. Visual Studios Settings 2

Click on Properties.

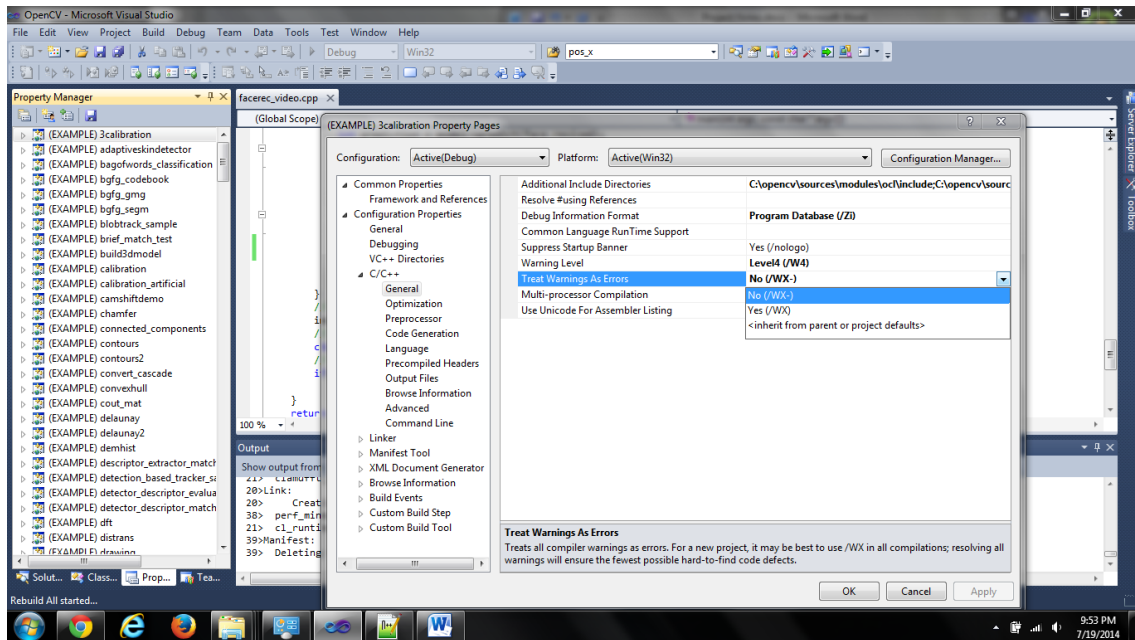


Figure 22. Visual Studios Settings 3

On new window, highlight file **(Example) facerec_video**. Click Configuration Properties->C/C++->General. Change “**Treat Warnings As Errors**” to “**No**”. Next change back to Solutions tab. Now build the solution.

- The next step is to put together a collection of images for training. Some sample images of celebrities were taken from offline and used. Additional photos were taken of other test subjects to use as training data. The images were edited by cropping out each image background other than the face. A program called IrfanView, which can be downloaded from many different repositories at http://www.irfanview.com/main_download_engl.htm, was used to edit the size of the images and make them square at 200x200 pixels.

3. After the images have been edited, a text (.txt) file needs to be created with the image location along with a label for the image. This is an example of what used for each line in the text file for this project: **C:\Pictures\Project2\Brad_Pitt_01.jpg;0**. For better training results, a large enough number of images per person needs to be used in order to accurately recognize an individual. This can be determined through trial and error. For this project, 50 images per subject were used.
4. At this point, the facial recognition application is able to be tested out. A command prompt needs to be opened and the following commands need to be entered and run **C:\OpenCV\binary5\bin\Debug\cpp-example-facerec_video.exe**
C:\opencv\sources\data\haarcascades\haarcascade_frontalface_default.xml C:\celebrities2.txt 1. This command will vary depending on what name was chosen for location to build the binaries in CMake, where the location of the **haarcascade_frontalface_default.xml** is, where the training images are stored, and the device number of the webcam.
5. To simplify the run process, the commands can be entered into a script file and the script file can be run rather, than having to run the commands each time. By default, the Fisherfaces method will be the one that is used for facial recognition.

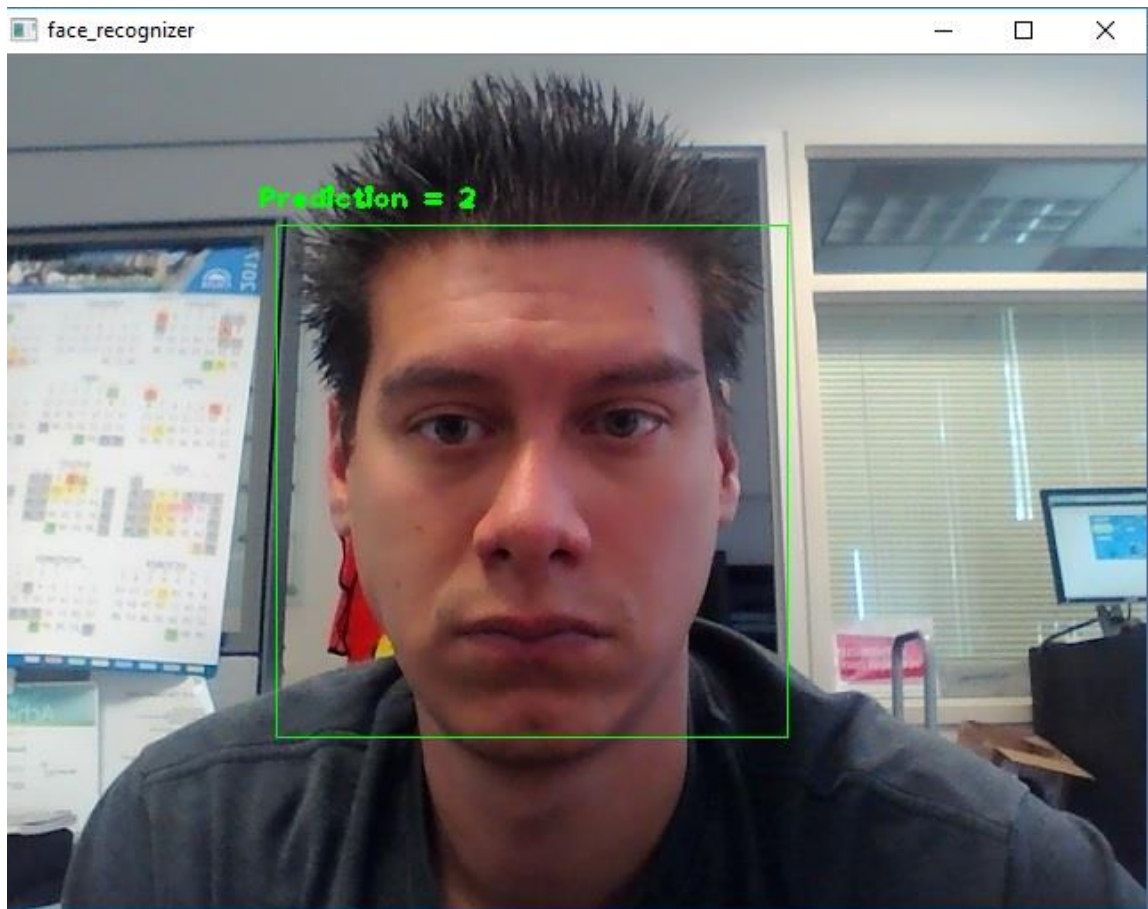


Figure 23. Prediction Image

The method used is changed in the **facerec_video.cpp** file. All of the code files were modified using Visual Studios. Below are the lines that need to be modified. Only one can be uncommented at a time.

```
// Create a FaceRecognizer and train it on the given images:  
Ptr<FaceRecognizer> model = createFisherFaceRecognizer();  
//Ptr<FaceRecognizer> model = createEigenFaceRecognizer();  
//Ptr<FaceRecognizer> model = createLBPHFaceRecognizer();
```

Figure 24. Facerec_video

A walkthrough can be found at

http://docs.opencv.org/2.4/modules/contrib/doc/facerec/facerec_tutorial.html#introduction.

Method Comparison Results

The process that was used to test the accuracy of the three different methods began with using three trials per method, per user. The testing was done at three different distances: 1.5 ft, 2.5 ft, and 3.5 ft. Facial position was another factor that was tested: straight, left side, right side. Each subject was tested for ten seconds in a still position. The prediction false positive rates were determined by the amount of time (in seconds) that the program displayed the false positives. This was presented as a percentage of the ten second trial (i.e., 8 seconds = 80%). The goal was to have the actual prediction results match the expected prediction results. The prediction results are integers that are labels and represent a person in the training data. Table 2 shows a list of the prediction results that of the subjects names associated with each integer label.

Table 2. Subject Labels

Integer Label	Person Name
0	Brad Pitt (Celebrity)
1	Reilly Flynn (Author's cousin)
2	Brandon Sierra (Author)
3	Angelina Jolie (Celebrity)
4	Jesse Pangelinan (Author's coworker)
5	Matt Marra (Author's coworker)

Definitions for table headers:

Expected Prediction Results – The integer label of the person being tested.

Actual Prediction Results – The integer label of the subject that the application was predicting the testing person was.

Prediction Rate (%) – The percentage rate at which the actual prediction results was correct.

False Positives Rate (%) – The percentage rate that the application falsely identified or recognized a face where a face was not present. (i.e., on a shirt, on a wall, etc.)

Note: A (-) in the results table means that no prediction could be determined at that time.

1:1 Facial Verification

The process of facial verification included Subject A in the training set and was tested against three different subjects. The first test was to determine if Subject A could be correctly identified in the *actual prediction* results by being verified for the maximum length of time during the testing period of 10 seconds. A longer verification time determined a higher prediction rate. When testing the other two subjects, verification should not occur, as their data was not included in the training set. The goal is to have the verification time of the other two subjects be as low as possible during the testing period. In this case, a shorter verification time determines a higher prediction rate. With the training set only containing one user, the Fisherfaces method was unable to be tested as it requires a minimum of two users. The comparison results of the testing can be seen in Table 3.

Table 3. 1:1 Eigenfaces vs Local Binary Pattern

Eigenfaces vs Local Binary Pattern Histogram						
Person 1:	Trial 1:	Position	Prediction Rate (%)		False Positive Rate (%)	
			Eigenfaces	LBPH	Eigenfaces	LBPH
		1.5 ft. Straight	100	100	20	5
		1.5 ft. Right Side	100	100	60	0
		1.5 ft. Left Side	40	100	30	0
		2.5 ft. Straight	100	100	70	100
		2.5 ft. Right Side	70	100	100	100
		2.5 ft. Left Side	10	100	80	70
		3.5 ft. Straight	100	100	20	80
		3.5 ft. Right Side	100	100	10	20
		3.5 ft. Left Side	10	100	70	80
	Trial 2:	1.5 ft. Straight	100	100	80	20
		1.5 ft. Right Side	95	100	10	5
		1.5 ft. Left Side	10	20	50	90
		2.5 ft. Straight	100	100	40	20
		2.5 ft. Right Side	100	100	60	80
		2.5 ft. Left Side	30	100	40	10
		3.5 ft. Straight	100	100	100	100
		3.5 ft. Right Side	90	100	10	20
		3.5 ft. Left Side	95	100	10	100
	Trial 3:	1.5 ft. Straight	100	100	100	0
		1.5 ft. Right Side	100	100	20	10
		1.5 ft. Left Side	0	80	10	80
		2.5 ft. Straight	100	100	100	70
		2.5 ft. Right Side	95	100	100	80
		2.5 ft. Left Side	0	100	100	10
		3.5 ft. Straight	100	100	10	30
		3.5 ft. Right Side	100	100	10	70
		3.5 ft. Left Side	80	100	20	50
Person 2:	Trial 1:	Position	Eigenfaces	LBPH	Eigenfaces	LBPH

		1.5 ft. Straight	0	0	0	100
		1.5 ft. Right Side	0	0	0	5
		1.5 ft. Left Side	100	0	0	20
		2.5 ft. Straight	0	0	0	0
		2.5 ft. Right Side	0	0	0	20
		2.5 ft. Left Side	0	0	0	0
		3.5 ft. Straight	0	0	0	0
		3.5 ft. Right Side	0	0	100	0
		3.5 ft. Left Side	0	0	0	0
	Trial 2:			0		
		1.5 ft. Straight	0	0	0	0
		1.5 ft. Right Side	0	0	20	0
		1.5 ft. Left Side	0	10	50	20
		2.5 ft. Straight	0	0	10	0
		2.5 ft. Right Side	0	0	10	0
		2.5 ft. Left Side	0	0	0	0
		3.5 ft. Straight	0	0	20	0
		3.5 ft. Right Side	0	0	20	0
		3.5 ft. Left Side	20	0	10	10
	Trial 3:					
		1.5 ft. Straight	0	0	10	0
		1.5 ft. Right Side	0	0	10	0
		1.5 ft. Left Side	0	0	10	0
		2.5 ft. Straight	0	0	0	0
		2.5 ft. Right Side	50	0	0	0
		2.5 ft. Left Side	100	0	10	0
		3.5 ft. Straight	0	0	0	0
		3.5 ft. Right Side	0	0	20	0
		3.5 ft. Left Side	0	30	10	0
Person 3:	Trial 1:	Position	Eigenfaces	LBPH	Eigenfaces	LBPH
		1.5 ft. Straight	0	0	10	0
		1.5 ft. Right Side	100	100	0	25
		1.5 ft. Left Side	50	50	80	50
		2.5 ft. Straight	0	0	0	20
		2.5 ft. Right Side	100	100	0	25
		2.5 ft. Left Side	100	50	20	20
		3.5 ft. Straight	0	0	0	0

Trial 2:	3.5 ft. Right Side	100	0	20	0
	3.5 ft. Left Side	100	0	100	0
	1.5 ft. Straight	0	0	20	10
	1.5 ft. Right Side	100	100	20	0
	1.5 ft. Left Side	100	100	30	80
	2.5 ft. Straight	0	0	0	0
	2.5 ft. Right Side	100	20	0	10
	2.5 ft. Left Side	0	0	25	0
	3.5 ft. Straight	0	0	10	0
	3.5 ft. Right Side	0	50	10	0
	3.5 ft. Left Side	75	50	20	20
	1.5 ft. Straight	0	0	0	0
	1.5 ft. Right Side	100	100	10	100
	1.5 ft. Left Side	25	100	20	100
	2.5 ft. Straight	0	0	0	0
	2.5 ft. Right Side	100	100	0	10
	2.5 ft. Left Side	50	100	80	100
	3.5 ft. Straight	0	0	0	0
	3.5 ft. Right Side	100	100	0	0
	3.5 ft. Left Side	100	100	80	100

In these results, it shows that the Eigenfaces and Local Binary Pattern Histogram original performed similarly in regard to both the detection rate and false positive rate. When testing the Local Binary Pattern Histogram modified compared to the original, the prediction rates were similar; however, the false positive rates decreased for the modified method (see Table 4).

Table 4. 1:1 Local Binary Pattern Original vs Local Binary Pattern Modified

Local Binary Pattern Histogram Original vs Local Binary Pattern Modified						
Person 1:	Trial 1:	Position	Prediction Rate (%)		False Positive Rate (%)	
			LBPH Original	LBPH Modified	LBPH Original	LBPH Modified
		1.5 ft. Straight	100	100	5	5
		1.5 ft. Right Side	100	100	0	0
		1.5 ft. Left Side	100	100	0	0
		2.5 ft. Straight	100	100	100	0
		2.5 ft. Right Side	100	100	100	80
		2.5 ft. Left Side	100	100	70	20
		3.5 ft. Straight	100	100	80	20
		3.5 ft. Right Side	100	100	20	20
		3.5 ft. Left Side	100	60	80	30
	Trial 2:	1.5 ft. Straight	100	100	20	100
		1.5 ft. Right Side	100	10	5	60
		1.5 ft. Left Side	20	100	90	60
		2.5 ft. Straight	100	100	20	95
		2.5 ft. Right Side	100	100	80	20
		2.5 ft. Left Side	100	100	10	90
		3.5 ft. Straight	100	100	100	90
		3.5 ft. Right Side	100	80	20	80
		3.5 ft. Left Side	100	95	100	10
	Trial 3:	1.5 ft. Straight	100	100	0	100
		1.5 ft. Right Side	100	100	10	100
		1.5 ft. Left Side	80	95	80	70
		2.5 ft. Straight	100	100	70	95
		2.5 ft. Right Side	100	100	80	100
		2.5 ft. Left Side	100	70	10	90
		3.5 ft. Straight	100	100	30	5

		3.5 ft. Right Side	100	100	70	70
		3.5 ft. Left Side	100	100	50	95
Person 2:	Trial 1:	Position	LBPH Original	LBPH Modified	LBPH Original	LBPH Modified
		1.5 ft. Straight	0	0	10	0
		1.5 ft. Right Side	0	0	0	20
		1.5 ft. Left Side	0	20	10	50
		2.5 ft. Straight	0	0	10	0
		2.5 ft. Right Side	0	20	30	0
		2.5 ft. Left Side	0	0	20	0
		3.5 ft. Straight	0	0	0	0
		3.5 ft. Right Side	0	0	0	0
		3.5 ft. Left Side	0	0	50	0
			0			
	Trial 2:	1.5 ft. Straight	0	0	0	0
		1.5 ft. Right Side	0	0	0	0
		1.5 ft. Left Side	10	0	0	0
		2.5 ft. Straight	0	0	20	0
		2.5 ft. Right Side	0	0	0	10
		2.5 ft. Left Side	0	0	0	10
		3.5 ft. Straight	0	0	20	10
		3.5 ft. Right Side	0	0	10	0
		3.5 ft. Left Side	0	0	20	0
	Trial 3:	1.5 ft. Straight	0	0	20	0
		1.5 ft. Right Side	0	0	10	0
		1.5 ft. Left Side	0	0	20	0
		2.5 ft. Straight	0	0	30	0
		2.5 ft. Right Side	0	0	20	0
		2.5 ft. Left Side	0	0	10	0
		3.5 ft. Straight	0	0	0	0
		3.5 ft. Right Side	0	0	90	5

		3.5 ft. Left Side	30	0	0	0
Person 3:	Trial 1:	Position	LBPH Original	LBPH Modified	LBPH Original	LBPH Modified
		1.5 ft. Straight	0	0	20	0
		1.5 ft. Right Side	100	100	10	20
		1.5 ft. Left Side	50	25	30	100
		2.5 ft. Straight	0	0	10	0
		2.5 ft. Right Side	100	100	20	30
		2.5 ft. Left Side	50	25	20	85
		3.5 ft. Straight	0	0	10	0
		3.5 ft. Right Side	0	100	50	0
		3.5 ft. Left Side	0	50	20	0
	Trial 2:					
		1.5 ft. Straight	0	0	20	0
		1.5 ft. Right Side	100	75	15	20
		1.5 ft. Left Side	100	0	60	80
		2.5 ft. Straight	0	0	10	0
		2.5 ft. Right Side	20	100	10	50
		2.5 ft. Left Side	0	0	5	20
		3.5 ft. Straight	0	0		10
		3.5 ft. Right Side	50	100	20	20
		3.5 ft. Left Side	50	0	5	80
	Trial 3:					
		1.5 ft. Straight	0	0	30	10
		1.5 ft. Right Side	100	25	20	0
		1.5 ft. Left Side	100	10	100	10
		2.5 ft. Straight	0	0	0	0
		2.5 ft. Right Side	100	75	40	10
		2.5 ft. Left Side	100	0	0	0
		3.5 ft. Straight	0	0	0	10
		3.5 ft. Right Side	100	100	0	10
		3.5 ft. Left Side	100	0	0	0

1:N Facial Identification

The process of facial identification included seven subjects in the training set and was tested against four subjects. The testing included verifying if each subject could be correctly identified in the actual prediction results by being correctly identified for as long as possible during the ten seconds tested. This would result in a higher prediction rate. The comparison results of the testing can be seen in Table 5.

Table 5. 1:N Eigenfaces vs Fisherfaces vs Local Binary Pattern

Eigenfaces vs Fisherfaces vs Local Binary Pattern Histogram								
Person 1:	Trial 1:	Position	Prediction Rate (%)			False Positive Rate (%)		
			Eigenface s	Fisherface s	LBP H	Eigenface s	Fisherface s	LBP H
		1.5 ft. Straight	100	30	0	10	20	0
		1.5 ft. Right Side	0	-	-	90	20	10
		1.5 ft. Left Side	80	-	0	30	10	10
		2.5 ft. Straight	90	20	0	20	50	0
		2.5 ft. Right Side	0	60	-	70	10	30
		2.5 ft. Left Side	100	-	-	30	5	0
		3.5 ft. Straight	100	80	30	90	100	10
		3.5 ft. Right Side	95	0	-	40	95	20
		3.5 ft. Left Side	10	95	100	20	10	10
	Trial 2:	1.5 ft. Straight	95	0	30	10	10	5
		1.5 ft. Right Side	100	-	-	90	10	10
		1.5 ft. Left Side	90	-	0	60	10	10
		2.5 ft. Straight	100	50	20	70	5	30

Trial 3:	2.5 ft. Right Side	70	60	-	30	80	60
	2.5 ft. Left Side	20	-	20	40	20	10
	3.5 ft. Straight	95	50	0	20	30	10
	3.5 ft. Right Side	100	30	0	10	90	10
	3.5 ft. Left Side	10	100	50	10	20	0
	1.5 ft. Straight	100	0	30	20	5	0
	1.5 ft. Right Side	50	-	-	10	10	10
	1.5 ft. Left Side	100	-	-	20	5	20
	2.5 ft. Straight	100	60	5	30	20	30
	2.5 ft. Right Side	100	10	-	20	40	60
	2.5 ft. Left Side	100	40	40	20	10	20
	3.5 ft. Straight	00	50	0	20	100	20
	3.5 ft. Right Side	00	0	-	30	100	80
	3.5 ft. Left Side	100	100	5	30	20	40

Person 2:	Trial 1:	Position	Eigenface s	Fisherface s	LBP H	Eigenface s	Fisherface s	LBP H
		1.5 ft. Straight	0	0	0	10	0	10
		1.5 ft. Right Side	0	0	-	60	5	0
		1.5 ft. Left Side	0	-	0	10	20	10
		2.5 ft. Straight	0	0	0	5	20	10
		2.5 ft. Right Side	0	0	0	60	15	30
		2.5 ft. Left Side	0	0	0	0	5	20
		3.5 ft. Straight	0	0	0	10	5	0
		3.5 ft. Right Side	0	0	0	0	20	0
		3.5 ft. Left Side	0	0	0	0	0	50
	Trial 2:	1.5 ft. Straight	0	0	0	5	0	0

Trial 3:	1.5 ft. Right Side	0	-	0	5	5	0
	1.5 ft. Left Side	0	0	0	60	20	0
	2.5 ft. Straight	0	0	0	0	20	20
	2.5 ft. Right Side	-	0	0	50	50	0
	2.5 ft. Left Side	0	0	-	10	5	0
	3.5 ft. Straight	0	0	0	40	0	20
	3.5 ft. Right Side	0	0	0	50	15	10
	3.5 ft. Left Side	0	0	0	20	10	20
	1.5 ft. Straight	0	0	0	0	30	20
	1.5 ft. Right Side	0	0	0	0	0	10
	1.5 ft. Left Side	0	0	0	10	20	20
	2.5 ft. Straight	0	0	0	5	0	30
	2.5 ft. Right Side	0	0	0	5	0	20
	2.5 ft. Left Side	0	0	0	15	0	10
	3.5 ft. Straight	0	0	0	0	20	0
	3.5 ft. Right Side	0	0	0	100	0	90
	3.5 ft. Left Side	0	0	0	100	20	0

Person 3:	Trial 1:	Position	Eigenface s	Fisherface s	LBP H	Eigenface s	Fisherface s	LBP H
		1.5 ft. Straight	0	0	30	10	20	20
		1.5 ft. Right Side	-	0	-	60	20	10
		1.5 ft. Left Side	0	0	-	10	40	30
		2.5 ft. Straight	25	0	0	20	40	10
		2.5 ft. Right Side	0	50	-	15	10	20
		2.5 ft. Left Side	0	0	-	60	0	20
		3.5 ft. Straight	30	0	0	40	20	10
		3.5 ft. Right Side	100	25	0	0	10	50

Trial 2:	3.5 ft. Left Side	0	-	-	0	0	20
	1.5 ft. Straight	0	0	30	0	30	20
	1.5 ft. Right Side	0	0	-	60	0	15
	1.5 ft. Left Side	0	0	-	100	20	60
	2.5 ft. Straight	60	0	50	60	100	10
	2.5 ft. Right Side	0	75	-	10	0	10
	2.5 ft. Left Side	0	0	-	100	60	5
	3.5 ft. Straight	75	0	30	80	70	
	3.5 ft. Right Side	100	50	0	50	0	20
	3.5 ft. Left Side	90	-	-	60	20	5
	1.5 ft. Straight	0	0	20	0	60	30
	1.5 ft. Right Side	0	0	0	0	0	20
	1.5 ft. Left Side	0	0	0	50	50	100
	2.5 ft. Straight	25	0	10	10	0	0
	2.5 ft. Right Side	100	50	0	60	0	40
Trial 3:	2.5 ft. Left Side	0	-	-	10	0	0
	3.5 ft. Straight	75	0	0	10	60	0
	3.5 ft. Right Side	-	100	0	20	0	0
	3.5 ft. Left Side	100	0	-	10	10	0

Person 4:	Trial 1:	Position	Eigenface s	Fisherface s	LBP H	Eigenface s	Fisherface s	LBP H
		1.5 ft. Straight	100	90	100	60	10	100
		1.5 ft. Right Side	100	100	90	0	90	0
		1.5 ft. Left Side	0	0	100	60	90	30
		2.5 ft. Straight	100	0	100	0	100	5
		2.5 ft. Right Side	100	50	100	0	10	0

Trial 2:	2.5 ft. Left Side	-	75	-	50	30	0
	3.5 ft. Straight	100	0	100	50	30	0
	3.5 ft. Right Side	75	75	-	20	100	70
	3.5 ft. Left Side	-	100	-	50	100	5
	1.5 ft. Straight	100	100	100	5	0	90
	1.5 ft. Right Side	70	100	100	60	60	40
	1.5 ft. Left Side	-	50	50	20	50	0
	2.5 ft. Straight	100	60	100	50	25	60
	2.5 ft. Right Side	0	100	100	60	70	20
	2.5 ft. Left Side	-	60	100	0	60	50
	3.5 ft. Straight	100	0	100	0	90	0
	3.5 ft. Right Side	0	90	100	10	20	70
	3.5 ft. Left Side	-	100	-	50	20	20
Trial 3:							
	1.5 ft. Straight	100	75	100	20	10	100
	1.5 ft. Right Side	0	75	100	20	50	50
	1.5 ft. Left Side	-	0	100	10	75	40
	2.5 ft. Straight	100	0	100	100	5	100
	2.5 ft. Right Side	100	50	100	0	50	0
	2.5 ft. Left Side	-	90	100	0	10	50
	3.5 ft. Straight	100	0	100	0	0	10
	3.5 ft. Right Side	0	100	100	10	50	90
	3.5 ft. Left Side	-	-	100	0	50	20

In these results, it shows that the Eigenfaces method performed the best between Eigenfaces, Fisherfaces, and Local Binary Pattern Histogram original in regard to the detection rate. However, the Eigenfaces method also had the largest false positive rate. The Local Binary Pattern Histogram original had the lowest prediction rate, while also having the lowest false positive rate. For this reason, the Local Binary Pattern Histogram was determined to be the best method to test an improvement on the algorithm. After the improvements, the Local Binary Pattern Histogram had both a higher prediction rate and a higher false positive rate. The prediction rate percentage increased for three of the four users tested. There were also fewer occurrences where the prediction rate was 0% correct (see Table 6).

Table 6. 1:N Local Binary Pattern Original vs Local Binary Pattern Modified

Local Binary Pattern Histogram Original vs Local Binary Pattern Modified						
Person 1:	Trial 1:	Position	Prediction Rate (%)		False Positive Rate (%)	
			LBPH Original	LBPH Modified	LBPH Original	LBPH Modified
		1.5 ft. Straight	0	40	0	20
		1.5 ft. Right Side	-	20	10	40
		1.5 ft. Left Side	0	0	10	80
		2.5 ft. Straight	0	50	0	30
		2.5 ft. Right Side	-	40	30	10
		2.5 ft. Left Side	-	0	0	40
		3.5 ft. Straight	30	0	10	20
		3.5 ft. Right Side	-	0	20	10
		3.5 ft. Left Side	100	5	10	30

Trial**2:**

1.5 ft. Straight	30	10	5	60
1.5 ft. Right Side	-	0	10	40
1.5 ft. Left Side	0	30	10	20
2.5 ft. Straight	20	10	30	40
2.5 ft. Right Side	-	20	60	30
2.5 ft. Left Side	20	0	10	20
3.5 ft. Straight	0	30	10	80
3.5 ft. Right Side	0	0	10	20
3.5 ft. Left Side	50	30	0	10

Trial**3:**

1.5 ft. Straight	30	40	0	60
1.5 ft. Right Side	-	20	10	60
1.5 ft. Left Side	-	0	20	70
2.5 ft. Straight	5	0	30	30
2.5 ft. Right Side	-	40	60	20
2.5 ft. Left Side	40	0	20	40
3.5 ft. Straight	0	10	20	80
3.5 ft. Right Side	-	30	80	20
3.5 ft. Left Side	5	0	40	70

Person 2:	Trial 1:	Position	LBPH Original	LBPH Modified	LBPH Original	LBPH Modified
		1.5 ft. Straight	0	30	10	0
		1.5 ft. Right Side	-	0	0	5
		1.5 ft. Left Side	0	-	10	20
		2.5 ft. Straight	0	0	10	10
		2.5 ft. Right Side	0	0	30	5
		2.5 ft. Left Side	0	-	20	100
		3.5 ft. Straight	0	0	0	0
		3.5 ft. Right Side	0	25	0	20
		3.5 ft. Left Side	0	20	50	10

Trial 2:	1.5 ft. Straight	0	10	0	0
	1.5 ft. Right Side	0	0	0	0
	1.5 ft. Left Side	0	10	0	10
	2.5 ft. Straight	0	0	20	0
	2.5 ft. Right Side	0	0	0	10
	2.5 ft. Left Side	-	50	0	0
	3.5 ft. Straight	0	0	20	0
	3.5 ft. Right Side	0	10	10	0
	3.5 ft. Left Side	0	50	20	10
Trial 3:	1.5 ft. Straight	0	0	20	10
	1.5 ft. Right Side	0	40	10	0
	1.5 ft. Left Side	0	50	20	20
	2.5 ft. Straight	0	0	30	0
	2.5 ft. Right Side	0	50	20	10
	2.5 ft. Left Side	0	15	10	20
	3.5 ft. Straight	0	25	0	10
	3.5 ft. Right Side	0	20	90	5
	3.5 ft. Left Side	0	50	0	10

Person 3:	Trial 1:	Position	LBPH Original	LBPH Modified	LBPH Original	LBPH Modified
		1.5 ft. Straight	30	30	20	20
		1.5 ft. Right Side	-	50	10	0
		1.5 ft. Left Side	-	0	30	60
		2.5 ft. Straight	0	0	10	20
		2.5 ft. Right Side	-	60	20	10
		2.5 ft. Left Side	-	25	20	0
		3.5 ft. Straight	0	0	10	0
		3.5 ft. Right Side	0	0	50	0
		3.5 ft. Left Side	-	0	20	0
	Trial 2:	1.5 ft. Straight	30	90	20	15

1.5 ft. Right Side	-	30	15	10
1.5 ft. Left Side	-	0	60	100
2.5 ft. Straight	50	0	10	10
2.5 ft. Right Side	-	30	10	5
2.5 ft. Left Side	-	0	5	0
3.5 ft. Straight	30	75		10
3.5 ft. Right Side	0	25	20	5
3.5 ft. Left Side	-	20	5	5
Trial 3:				
1.5 ft. Straight	20	0	30	30
1.5 ft. Right Side	0	0	20	20
1.5 ft. Left Side	0	0	100	80
2.5 ft. Straight	10	0	0	20
2.5 ft. Right Side	0	50	40	10
2.5 ft. Left Side	-	0	0	0
3.5 ft. Straight	0	50	0	5
3.5 ft. Right Side	0	75	0	5
3.5 ft. Left Side	-	0	0	10

Person 4:	Trial 1:	Position	LBPH Original	LBPH Modified	LBPH Original	LBPH Modified
		1.5 ft. Straight	100	25	100	0
		1.5 ft. Right Side	90	0	0	0
		1.5 ft. Left Side	100	50	30	0
		2.5 ft. Straight	100	50	5	10
		2.5 ft. Right Side	100	0	0	0
		2.5 ft. Left Side	-	50	0	100
		3.5 ft. Straight	100	20	0	0
		3.5 ft. Right Side	-	15	70	5
		3.5 ft. Left Side	-	60	5	5
	Trial 2:					
		1.5 ft. Straight	100	60	90	100
		1.5 ft. Right Side	100	0	40	50

Trial 3:	1.5 ft. Left Side	50	0	0	100
	2.5 ft. Straight	100	50	60	0
	2.5 ft. Right				
	Side	100	0	20	10
	2.5 ft. Left Side	100	0	50	50
	3.5 ft. Straight	100	50	0	0
	3.5 ft. Right				
	Side	100	0	70	0
	3.5 ft. Left Side	-	75	20	0
	1.5 ft. Straight	100	15	100	10
	1.5 ft. Right				
	Side	100	60	50	20
	1.5 ft. Left Side	100	50	40	80
	2.5 ft. Straight	100	0	100	5
	2.5 ft. Right				
	Side	100	0	0	20
	2.5 ft. Left Side	100	60	50	100
	3.5 ft. Straight	100	0	10	0
	3.5 ft. Right				
	Side	100	30	90	0
	3.5 ft. Left Side	100	0	20	30

Implementation of Local Binary Pattern Histogram

On a human face, not all facial characteristics are equally identifiable by themselves. For example, if person A was shown only the forehead of person B, it is not very likely that person A would be able to easily distinguish person B from a group of people using the forehead alone to identify. The same can be said for other facial features, such as the cheeks. However, there are some facial features that play a greater role in being able to identify a person. These features could include eyes, nose, mouth, etc. Considering this nuance, one way

that the Local Binary Pattern Histogram could be improved upon is by adding weights to specific regions on a face. Each weight would be differentiated and determined by the contrast of gray scale values for each pixel and its neighbors. The weights would be calculated using the standard deviation method (see Figure 25). The weights would be calculated, and the weight of each region would be multiplied to the region matrix using the scalar multiplication method. Then, the region histograms would be concatenated into one large histogram where they can be rearranged to have the regions with the highest weights being pushed onto the matrix first. The region with the second highest regions would be pushed next, then the third, and so on. This process would continue until the lowest weight region was pushed onto the matrix last (see Figure 24). This would make the recognition process more accurate by forcing the regions with the higher weights to play a greater part in the identification process. The functions in Figures 26-27 were added and modified for this project. There will be comments that start with **// New:** followed by a description of what the code following does for the code that were added/modified.

LBPH Spatial Histogram (Modified) Flow Chart

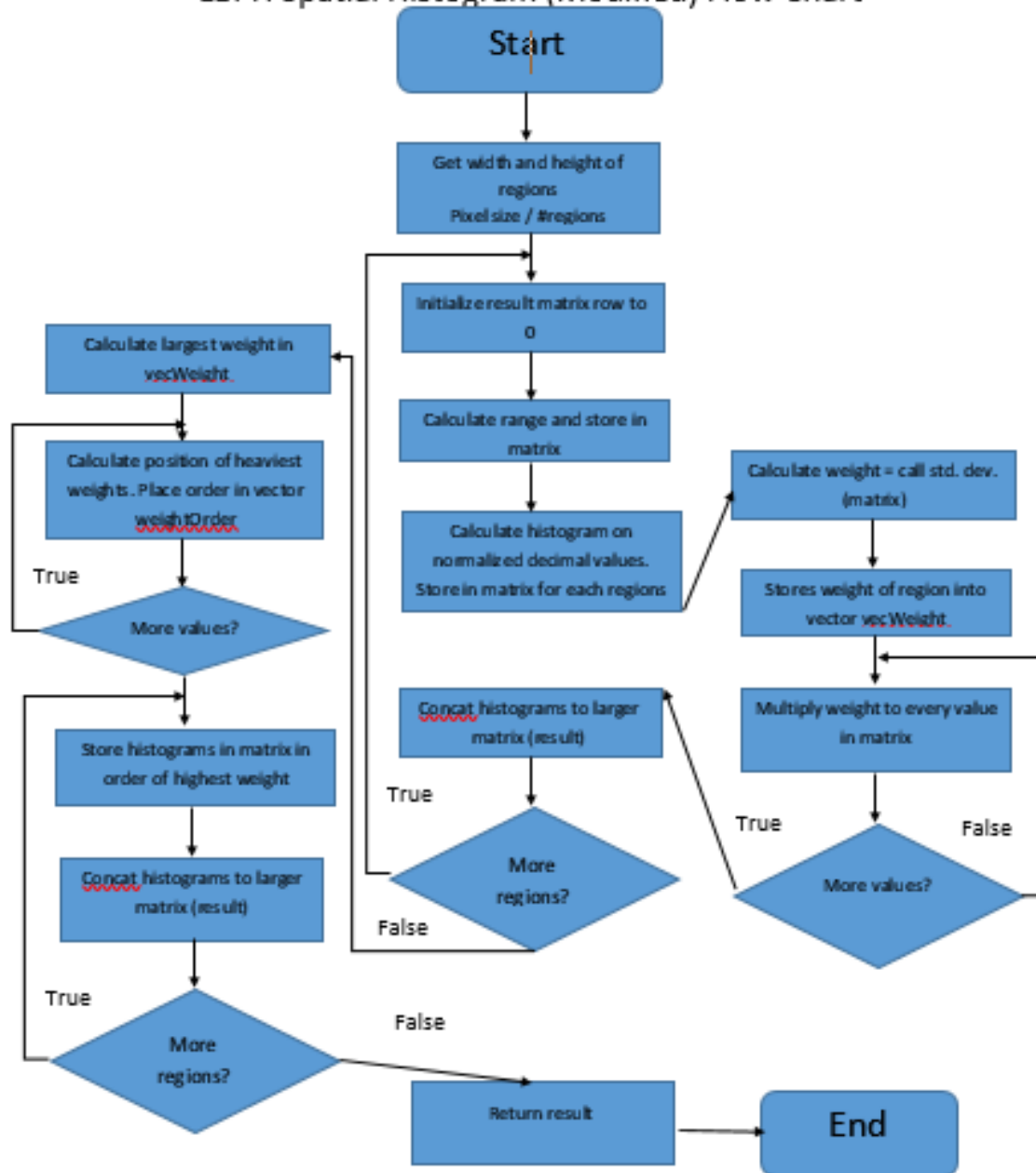


Figure 25. Local Binary Pattern Spatial Histogram (Modified) Flow Chart

LBPH Std. Deviation Flow Chart

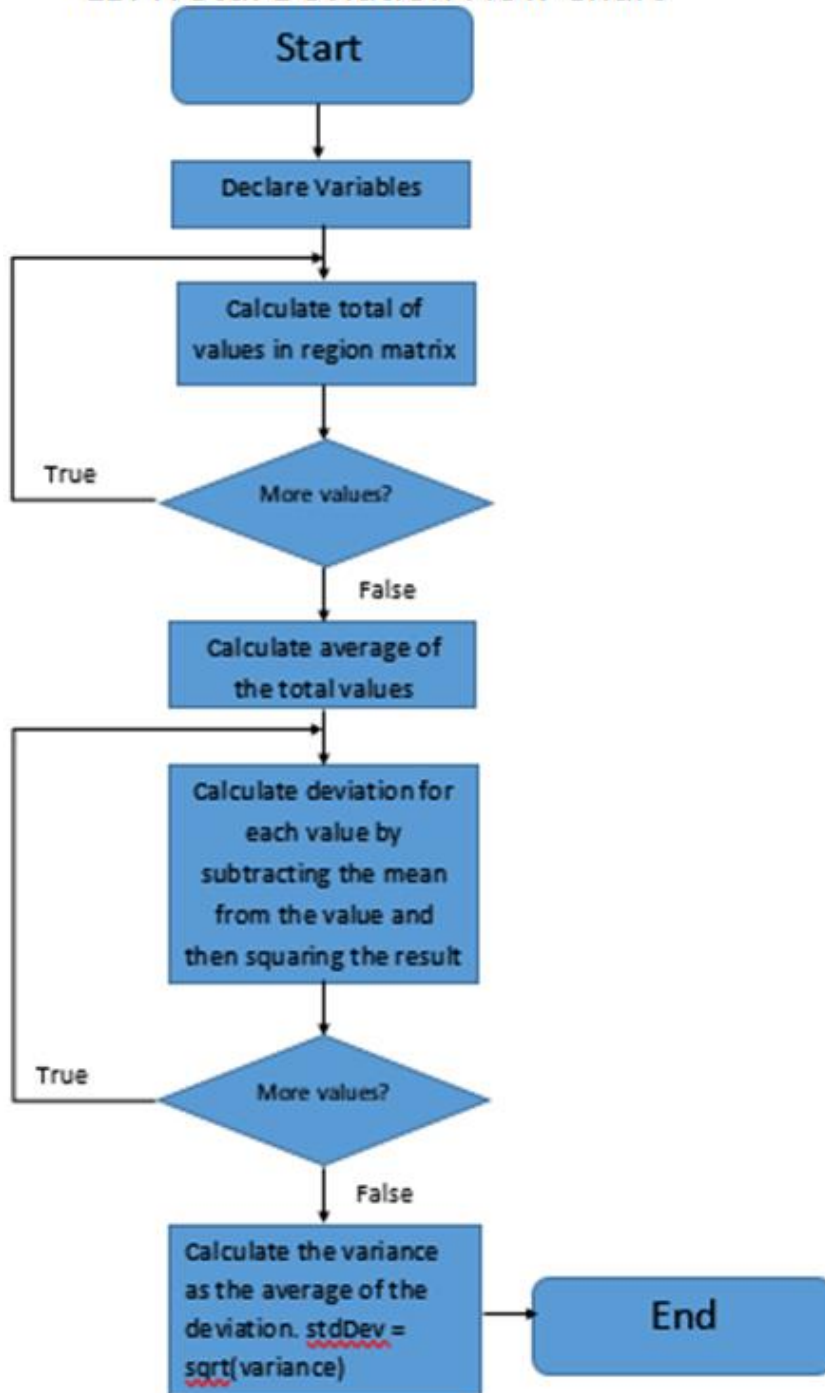


Figure 26. Local Binary Pattern Standard Deviation Flow Chart

```

/*****
*NEW FUNCTION
*Calculates the standard deviation for each region matrix and
*assigns the value as a weight.
*****/
static float standard_deviation(Mat input)
{
    float total;
    float totalDev;
    float mean;
    int i;
    float stdDev;

    for(i = 0; i < input.cols; i++)
    {
        total = input.at<float>(i);
    }

    mean = total / i;

    for(i = 0; i < input.cols; i++)
    {
        totalDev = (input.at<float>(i) - mean) * (input.at<float>(i) - mean);
    }

    stdDev = totalDev / i;

    return stdDev;
}

static Mat spatial_histogram(InputArray _src, int numPatterns,
                             int grid_x, int grid_y, bool /*normed*/)
{
    Mat src = _src.getMat();
    Mat result_row; //new
    Mat cell_hist; //new
    float weight; //new
    vector<float> vecWeight; //new

    // calculate LBP patch size
    int width = src.cols/grid_x;
    int height = src.rows/grid_y;
    // allocate memory for the spatial histogram
    Mat result = Mat::zeros(grid_x * grid_y, numPatterns, CV_32FC1);
    // return matrix with zeros if no data was given
    if(src.empty())
        return result.reshape(1,1);
    // initial result_row
    int resultRowIdx = 0;
    // iterate through grid
    for(int i = 0; i < grid_y; i++) {
        for(int j = 0; j < grid_x; j++) {
            Mat src_cell = Mat(src, Range(i*height,(i+1)*height), Range(j*width,(j+1)*width));

            cell_hist = histc(src_cell, 0, (numPatterns-1), true);

```

Figure 27. Local Binary Pattern Modified Source Code 1

```

// New: Calls the fuction to caculate each regions weight using standard deviation
weight = standard_deviation(cell_hist);
// New: The weight is added to a vector to keep track of the weight for all of the
regions in an image
vecWeight.push_back(weight);

// New: Uses scalar multiplication to multiply the regions weight to the region
matrix
for(int i = 0; i < cell_hist.cols; i++)
{
    cell_hist.at<float>(i) = cell_hist.at<float>(i) * weight;
}

// copy to the result matrix
result_row = result.row(resultRowIdx);
cell_hist.reshape(1,1).convertTo(result_row, CV_32FC1);
// increase row count in result matrix
resultRowIdx++;
}

// New: Calculates the maximum weight in the vecWeight vector
float it = *max_element(vecWeight.begin(), vecWeight.end());
vector<int> weightOrder;

// New: Calculates the position of the heaviest weights, and then places this order in a
vector.
// After the heaviest weight is used, it is assigned a -1 so that it is not used again.
while(it != -1)
{
    for(int i = 0; i < vecWeight.size(); i++)
    {
        if(vecWeight[i] == it)
        {
            weightOrder.push_back(i);
            vecWeight[i] = -1;
        }
    }
    it = *max_element(vecWeight.begin(), vecWeight.end());
}

// New: Places the regions in the result matrix based on the weight of the region
for(int i = 0; i < result.rows; i++)
{
    //copy to the result matrix
    resultRowIdx = weightOrder[i];
    result_row = result.row(resultRowIdx);
    cell_hist.reshape(1,1).convertTo(result_row, CV_32FC1);
}

//return result as reshaped feature vector
return result.reshape(1,1);

```

Figure 28. Local Binary Pattern Modified Source Code 2

CHAPTER FIVE

CONCLUSION AND FUTURE RESEARCH

The improvement to the Local Binary Pattern Histogram method for facial recognition is important due to the fact that each method has its advantages and disadvantages. It is extremely important that new methods are created and previous methods are continuously improved upon to make certain that facial recognition predictions are as accurate as possible. This is especially true with facial recognition being a form of biometric authentication that is increasing in popularity for facial verification and identification. If an optimal method could potentially be found, there could be possibly be an exponential increase in the popularity of facial recognition, along with increases in security, safety, and identification.

Another potential improvement to the Local Binary Pattern Histogram method in this project could be the option to disregard regions with a weight below a set threshold. During the process of building the image histogram by concatenating the regional histograms ordered by weights, it could be possible to not include histograms whose weights are below a specific threshold. This could increase the processing time it takes during the training portion. The concern would be if this would have any effect on the accuracy of the prediction rate as the training time is decreased.

APPENDIX A
1:N EIGENFACES RESULTS

Eigenface						
Person 1:	Trial 1:	Position	Expected Prediction Results	Actual Prediction Results	Prediction Rate (%)	False Positives Rate (%)
		1.5 ft. Straight	2	2	100	10
		1.5 ft. Right Side	2	5	0	90
		1.5 ft. Left Side	2	2	80	30
		2.5 ft. Straight	2	2/4	90	20
		2.5 ft. Right Side	2	0/5	0	70
		2.5 ft. Left Side	2	2	100	30
		3.5 ft. Straight	2	2	100	90
		3.5 ft. Right Side	2	0/2	95	40
		3.5 ft. Left Side	2	1/2/5	10	20
	Trial 2:	1.5 ft. Straight	2	2/4	95	10
		1.5 ft. Right Side	2	2	100	90
		1.5 ft. Left Side	2	2	90	60
		2.5 ft. Straight	2	2	100	70
		2.5 ft. Right Side	2	2/5	70	30
		2.5 ft. Left Side	2	1/2/5	20	40
		3.5 ft. Straight	2	2/5	95	20
		3.5 ft. Right Side	2	2	100	10
		3.5 ft. Left Side	2	2/5	10	10
	Trial 3:	1.5 ft. Straight	2	2	100	20
		1.5 ft. Right Side	2	0/2/5	50	10
		1.5 ft. Left Side	2	2	100	20
		2.5 ft. Straight	2	2	100	30
		2.5 ft. Right Side	2	2	100	20
		2.5 ft. Left Side	2	2	100	20
		3.5 ft. Straight	2	2	00	20
		3.5 ft. Right Side	2	2	00	30
		3.5 ft. Left Side	2	2	100	30
Person 2:	Trial 1:	Position	Expected Prediction Results	Actual Prediction Results	Prediction Rate (%)	False Positives Rate (%)
		1.5 ft. Straight	1	2	0	10
		1.5 ft. Right Side	1	4	0	60
		1.5 ft. Left Side	1	2	0	10
		2.5 ft. Straight	1	2	0	5
		2.5 ft. Right Side	1	2	0	60

	2.5 ft. Left Side	1	2	0	0
	3.5 ft. Straight	1	2	0	10
	3.5 ft. Right Side	1	2	0	0
	3.5 ft. Left Side	1	2	0	0
Trial 2:	1.5 ft. Straight	1	2	0	5
	1.5 ft. Right Side	1	2/4/5	0	5
	1.5 ft. Left Side	1	2/4/5	0	60
	2.5 ft. Straight	1	2	0	0
	2.5 ft. Right Side	1	-	-	50
	2.5 ft. Left Side	1	2	0	10
	3.5 ft. Straight	1	2/5	0	40
	3.5 ft. Right Side	1	2	0	50
	3.5 ft. Left Side	1	2	0	20
Trial 3:	1.5 ft. Straight	1	2	0	0
	1.5 ft. Right Side	1	0/5	0	0
	1.5 ft. Left Side	1	2	0	10
	2.5 ft. Straight	1	2	0	5
	2.5 ft. Right Side	1	2/5	0	5
	2.5 ft. Left Side	1	2	0	15
	3.5 ft. Straight	1	2/5	0	0
	3.5 ft. Right Side	1	2	0	100
	3.5 ft. Left Side	1	2	0	100

Person 3:	Trial 1:	Position	Expected Prediction Results	Actual Prediction Results	Prediction Rate (%)	False Positives Rate (%)
		1.5 ft. Straight	8	2/4	0	10
		1.5 ft. Right Side	8	-	-	60
		1.5 ft. Left Side	8	2	0	10
		2.5 ft. Straight	8	2/4/5	25	20
		2.5 ft. Right Side	8	0	0	15
		2.5 ft. Left Side	8	2	0	60
		3.5 ft. Straight	8	2/4/5	30	40
		3.5 ft. Right Side	8	5	100	0
		3.5 ft. Left Side	8	2	0	0
	Trial 2:	1.5 ft. Straight	8	4	0	0
		1.5 ft. Right Side	8	2	0	60
		1.5 ft. Left Side	8	0/2	0	100
		2.5 ft. Straight	8	4/5	60	60

Trial 3:	2.5 ft. Right Side	8	0	0	10
	2.5 ft. Left Side	8	2	0	100
	3.5 ft. Straight	8	4/5	75	80
	3.5 ft. Right Side	8	5	100	50
	3.5 ft. Left Side	8	2/5	90	60
	1.5 ft. Straight	8	7	0	0
	1.5 ft. Right Side	8	2	0	0
	1.5 ft. Left Side	8	2	0	50
	2.5 ft. Straight	8	2/4/5	25	10
	2.5 ft. Right Side	8	5	100	60
	2.5 ft. Left Side	8	2	0	10
	3.5 ft. Straight	8	4/5	75	10
	3.5 ft. Right Side	8	-	-	20
	3.5 ft. Left Side	8		8 100	10

Person 4:	Trial 1:	Position	Expected Prediction Results	Actual Prediction Results	Prediction Rate (%)	False Positives Rate (%)
		1.5 ft. Straight	0	0	100	60
		1.5 ft. Right Side	0	0	100	0
		1.5 ft. Left Side	0	2	0	60
		2.5 ft. Straight	0	0	100	0
		2.5 ft. Right Side	0	0	100	0
		2.5 ft. Left Side	0	-	-	50
		3.5 ft. Straight	0	0	100	50
		3.5 ft. Right Side	0	0/5	75	20
		3.5 ft. Left Side	0	-	-	50
	Trial 2:	1.5 ft. Straight	0	0	100	5
		1.5 ft. Right Side	0	0/5	70	60
		1.5 ft. Left Side	0	-	-	20
		2.5 ft. Straight	0	0	100	50
		2.5 ft. Right Side	0	2	0	60
		2.5 ft. Left Side	0	-	-	0
		3.5 ft. Straight	0	0	100	0
		3.5 ft. Right Side	0	2/5	0	10
		3.5 ft. Left Side	0	-	-	50
	Trial 3:	1.5 ft. Straight	0	0	100	20
		1.5 ft. Right Side	0	2/5	0	20

1.5 ft. Left Side	0	-	-	10
2.5 ft. Straight	0	0	100	100
2.5 ft. Right				
Side	0	0	100	0
2.5 ft. Left Side	0	-	-	0
3.5 ft. Straight	0	0	100	0
3.5 ft. Right				
Side	0	2/5	0	10
3.5 ft. Left Side	0	-	-	0

APPENDIX B

1:N FISHERFACES RESULTS

Fisherfaces						
Person 1:	Trial 1:	Position	Expected Prediction Results	Actual Prediction Results	Prediction Rate (%)	False Positives Rate (%)
		1.5 ft. Straight	2	2/4	30	20
		1.5 ft. Right Side	2	-	-	20
		1.5 ft. Left Side	2	-	-	10
		2.5 ft. Straight	2	1/2/4	20	50
		2.5 ft. Right Side	2	0/2	60	10
		2.5 ft. Left Side	2	-	-	5
		3.5 ft. Straight	2	2/4	80	100
		3.5 ft. Right Side	2	0/4	0	95
		3.5 ft. Left Side	2	2/5	95	10
	Trial 2:	1.5 ft. Straight	2	4	0	10
		1.5 ft. Right Side	2	-	-	10
		1.5 ft. Left Side	2	-	-	10
		2.5 ft. Straight	2	2/4	50	5
		2.5 ft. Right Side	2	2/4	60	80
		2.5 ft. Left Side	2	-	-	20
		3.5 ft. Straight	2	2/4	50	30
		3.5 ft. Right Side	2	2/4	30	90
		3.5 ft. Left Side	2	2	100	20
	Trial 3:	1.5 ft. Straight	2	4	0	5
		1.5 ft. Right Side	2	-	-	10
		1.5 ft. Left Side	2	-	-	5
		2.5 ft. Straight	2	2/4	60	20
		2.5 ft. Right Side	2	0/2/4	10	40
		2.5 ft. Left Side	2	2/4	40	10
		3.5 ft. Straight	2	2/5	50	100
		3.5 ft. Right Side	2	0/5	0	100
		3.5 ft. Left Side	2	2	100	20
Person 2:	Trial 1:	Position	Expected Prediction Results	Actual Prediction Results	Prediction Rate (%)	False Positives Rate (%)
		1.5 ft. Straight	1	2	0	0
		1.5 ft. Right Side	1	0/2	0	5
		1.5 ft. Left Side	1	-	-	20
		2.5 ft. Straight	1	2/4	0	20
		2.5 ft. Right Side	1	0/4/5	0	15

Trial 2:	2.5 ft. Left Side	1	2/4/5	0	5
	3.5 ft. Straight	1	2	0	5
	3.5 ft. Right Side	1	0/5	0	20
	3.5 ft. Left Side	1	2	0	0
	1.5 ft. Straight	1	2	0	0
	1.5 ft. Right Side	1	-	-	5
	1.5 ft. Left Side	1	2	0	20
	2.5 ft. Straight	1	0/4	0	20
	2.5 ft. Right Side	1	0	0	50
	2.5 ft. Left Side	1	2	0	5
	3.5 ft. Straight	1	0/2/5	0	0
	3.5 ft. Right Side	1	0/5	0	15
	3.5 ft. Left Side	1	2/4	0	10
Trial 3:	1.5 ft. Straight	1	2/4	0	30
	1.5 ft. Right Side	1	0/5	0	0
	1.5 ft. Left Side	1	2/5	0	20
	2.5 ft. Straight	1	4	0	0
	2.5 ft. Right Side	1	5	0	0
	2.5 ft. Left Side	1	0/2	0	0
	3.5 ft. Straight	1	0/2/4	0	20
	3.5 ft. Right Side	1	0/5	0	0
	3.5 ft. Left Side	1	2	0	20

Person 3:	Trial 1:	Position	Expected Prediction Results	Actual Prediction Results	Prediction Rate (%)	False Positives Rate (%)
		1.5 ft. Straight	8	2/4	0	20
		1.5 ft. Right Side	8	3/4	0	20
		1.5 ft. Left Side	8	3/4	0	40
		2.5 ft. Straight	8	2	0	40
		2.5 ft. Right Side	8	0/5	50	10
		2.5 ft. Left Side	8	3/4	0	0
		3.5 ft. Straight	8	2	0	20
		3.5 ft. Right Side	8	0/3/4/5	25	10
		3.5 ft. Left Side	8	-	-	0
Trial 2:		1.5 ft. Straight	8	0/2/4	0	30
		1.5 ft. Right Side	8	3	0	0
		1.5 ft. Left Side	8	2/3/4	0	20
		2.5 ft. Straight	8	0	0	100

Trial 3:	2.5 ft. Right Side	8	0/4/5	75	0
	2.5 ft. Left Side	8	7	0	60
	3.5 ft. Straight	8	2	0	70
	3.5 ft. Right Side	8	0/3/4/5	50	0
	3.5 ft. Left Side	8	-	-	20
	1.5 ft. Straight	8	2	0	60
	1.5 ft. Right Side	8	0/4	0	0
	1.5 ft. Left Side	8	3/4	0	50
	2.5 ft. Straight	8	2/4	0	0
	2.5 ft. Right Side	8	0/5	50	0
	2.5 ft. Left Side	8	-	-	0
	3.5 ft. Straight	8	0/2	0	60
	3.5 ft. Right Side	8	5	100	0
	3.5 ft. Left Side	8	2/3/4	0	10

Person 4:	Trial 1:	Position	Expected Prediction Results	Actual Prediction Results	Prediction Rate (%)	False Positives Rate (%)
		1.5 ft. Straight	0	0/5	90	10
		1.5 ft. Right Side	0	0	100	90
		1.5 ft. Left Side	0	2	0	90
		2.5 ft. Straight	0	4	0	100
		2.5 ft. Right Side	0	0/5	50	10
		2.5 ft. Left Side	0	0/2/5	75	30
		3.5 ft. Straight	0	4	0	30
		3.5 ft. Right Side	0	0/5	75	100
		3.5 ft. Left Side	0	0	100	100
	Trial 2:	1.5 ft. Straight	0	0	100	0
		1.5 ft. Right Side	0	0	100	60
		1.5 ft. Left Side	0	0/2/5	50	50
		2.5 ft. Straight	0	0/4	60	25
		2.5 ft. Right Side	0	0	100	70
		2.5 ft. Left Side	0	0/2/5	60	60
		3.5 ft. Straight	0	4	0	90
		3.5 ft. Right Side	0	0/5	90	20
		3.5 ft. Left Side	0	0	100	20
	Trial 3:	1.5 ft. Straight	0	0/5	75	10
		1.5 ft. Right Side	0	0/2	75	50

1.5 ft. Left Side	0	5	0	75
2.5 ft. Straight	0	4	0	5
2.5 ft. Right				
Side	0	0/5	50	50
2.5 ft. Left Side	0	0/2	90	10
3.5 ft. Straight	0	4	0	0
3.5 ft. Right				
Side	0	0	100	50
3.5 ft. Left Side	0	-	-	50

APPENDIX C

1:N LOCAL BINARY PATTERN (ORIGINAL) RESULTS

Local Binary Pattern Histogram (Original)						
Person 1:	Trial 1:	Position	Expected Prediction Results	Actual Prediction Results	Prediction Rate (%)	False Positives Rate (%)
	Trial 1:	1.5 ft. Straight	2	4/5	0	0
		1.5 ft. Right Side	2	-	-	10
		1.5 ft. Left Side	2	4	0	10
		2.5 ft. Straight	2	4/5	0	0
		2.5 ft. Right Side	2	-	-	30
		2.5 ft. Left Side	2	4/5	-	0
		3.5 ft. Straight	2	0/2/5	30	10
		3.5 ft. Right Side	2	-	-	20
		3.5 ft. Left Side	2	2	100	10
	Trial 2:	1.5 ft. Straight	2	2/4/5	30	5
		1.5 ft. Right Side	2	-	-	10
		1.5 ft. Left Side	2	4/5	0	10
		2.5 ft. Straight	2	0/2/5	20	30
		2.5 ft. Right Side	2	-	-	60
		2.5 ft. Left Side	2	2/4/5	20	10
		3.5 ft. Straight	2	0/5	0	10
		3.5 ft. Right Side	2	4	0	10
		3.5 ft. Left Side	2	2/4/5	50	0
	Trial 3:	1.5 ft. Straight	2	0/4/5	30	0
		1.5 ft. Right Side	2	-	-	10
		1.5 ft. Left Side	2	-	-	20
		2.5 ft. Straight	2	42771	5	30
		2.5 ft. Right Side	2	-	-	60
		2.5 ft. Left Side	2	38387	40	20
		3.5 ft. Straight	2	0/5	0	20
		3.5 ft. Right Side	2	-	-	80
		3.5 ft. Left Side	2	38387	5	40
Person 2:	Trial 1:	Position	Expected Prediction Results	Actual Prediction Results	Prediction Rate (%)	False Positives Rate (%)
		1.5 ft. Straight	1	3/8	0	10
		1.5 ft. Right Side	1	-	-	0
		1.5 ft. Left Side	1	0/4/5	0	10
		2.5 ft. Straight	1	5	0	10
		2.5 ft. Right Side	1	5	0	30

Trial 2:	2.5 ft. Left Side	1	0/4	0	20
	3.5 ft. Straight	1	0/5	0	0
	3.5 ft. Right Side	1	0/4	0	0
	3.5 ft. Left Side	1	2/4/5	0	50
	1.5 ft. Straight	1	2/4/5	0	0
	1.5 ft. Right Side	1	-	0	0
	1.5 ft. Left Side	1	4	0	0
	2.5 ft. Straight	1	2/4/5	0	20
	2.5 ft. Right Side	1	5	0	0
	2.5 ft. Left Side	1	-	-	0
	3.5 ft. Straight	1	0	0	20
	3.5 ft. Right Side	1	4/5	0	10
	3.5 ft. Left Side	1	4	0	20
Trial 3:	1.5 ft. Straight	1	5	0	20
	1.5 ft. Right Side	1	-	0	10
	1.5 ft. Left Side	1	-	0	20
	2.5 ft. Straight	1	0/3/5	0	30
	2.5 ft. Right Side	1	4	0	20
	2.5 ft. Left Side	1	4	0	10
	3.5 ft. Straight	1	0/3/4/5	0	0
	3.5 ft. Right Side	1	0/4	0	90
	3.5 ft. Left Side	1	4	0	0

Person 3:	Trial 1:	Position	Expected Prediction Results	Actual Prediction Results	Prediction Rate (%)	False Positives Rate (%)
		1.5 ft. Straight	5	0/4/5	30	20
		1.5 ft. Right Side	5	-	-	10
		1.5 ft. Left Side	5	-	-	30
		2.5 ft. Straight	5	0/4	0	10
		2.5 ft. Right Side	5	-	-	20
		2.5 ft. Left Side	5	-	-	20
		3.5 ft. Straight	5	0	0	10
		3.5 ft. Right Side	5	0	0	50
		3.5 ft. Left Side	5	-	-	20
	Trial 2:	1.5 ft. Straight	5	4/5	30	20
		1.5 ft. Right Side	5	-	-	15
		1.5 ft. Left Side	5	-	-	60
		2.5 ft. Straight	5	0/2/4/5	50	10

	2.5 ft. Right Side	5	-	-	10
	2.5 ft. Left Side	5	-	-	5
	3.5 ft. Straight	5	0/5	30	
	3.5 ft. Right Side	5	4	0	20
	3.5 ft. Left Side	5	-	-	5
Trial 3:	1.5 ft. Straight	5	0/4/5	20	30
	1.5 ft. Right Side	5	0	0	20
	1.5 ft. Left Side	5	0	0	100
	2.5 ft. Straight	5	0/4/5	10	0
	2.5 ft. Right Side	5	0	0	40
	2.5 ft. Left Side	5	-	-	0
	3.5 ft. Straight	5	0	0	0
	3.5 ft. Right Side	5	0	0	0
	3.5 ft. Left Side	5	-	-	0

Person 4:	Trial 1:	Position	Expected Prediction Results	Actual Prediction Results	Prediction Rate (%)	False Positives Rate (%)
		1.5 ft. Straight	0	0	100	100
		1.5 ft. Right Side	0	0/4	90	0
		1.5 ft. Left Side	0	0	100	30
		2.5 ft. Straight	0	0	100	5
		2.5 ft. Right Side	0	0	100	0
		2.5 ft. Left Side	0	-	-	0
		3.5 ft. Straight	0	0	100	0
		3.5 ft. Right Side	0	-	-	70
		3.5 ft. Left Side	0	-	-	5
Trial 2:		1.5 ft. Straight	0	0	100	90
		1.5 ft. Right Side	0	0	100	40
		1.5 ft. Left Side	0	0/2/4	50	0
		2.5 ft. Straight	0	0	100	60
		2.5 ft. Right Side	0	0	100	20
		2.5 ft. Left Side	0	0	100	50
		3.5 ft. Straight	0	0	100	0
		3.5 ft. Right Side	0	0	100	70
		3.5 ft. Left Side	0	-	-	20
Trial 3:		1.5 ft. Straight	0	0	100	100
		1.5 ft. Right Side	0	0	100	50

1.5 ft. Left Side	0	0	100	40
2.5 ft. Straight	0	0	100	100
2.5 ft. Right				
Side	0	0	100	0
2.5 ft. Left Side	0	0	100	50
3.5 ft. Straight	0	0	100	10
3.5 ft. Right				
Side	0	0	100	90
3.5 ft. Left Side	0	0	100	20

APPENDIX D

1:N LOCAL BINARY PATTERN (MODIFIED) RESULTS

Local Binary Pattern Histogram (Modified)					
Person 1:	Trial 1:	Position	Expected Prediction Results	Actual Prediction Results	Prediction Rate (%) False Positives Rate (%)
		1.5 ft. Straight	2	0/2/3	40
		1.5 ft. Right Side	2	2/3/4	20
		1.5 ft. Left Side	2	1/4	0
		2.5 ft. Straight	2	1/2/4	50
		2.5 ft. Right Side	2	2/3/4	40
		2.5 ft. Left Side	2	3/4/5	0
		3.5 ft. Straight	2	1/3/4/5	0
		3.5 ft. Right Side	2	4	0
		3.5 ft. Left Side	2	1/2	5
	Trial 2:	1.5 ft. Straight	2	2/3/4	10
		1.5 ft. Right Side	2	3/4	0
		1.5 ft. Left Side	2	0/2/3	30
		2.5 ft. Straight	2	2/3	10
		2.5 ft. Right Side	2	2/3/4	20
		2.5 ft. Left Side	2	0/3	0
		3.5 ft. Straight	2	1/2/3/5	30
		3.5 ft. Right Side	2	0/3/4	0
		3.5 ft. Left Side	2	2/3/4	30
	Trial 3:	1.5 ft. Straight	2	2/4	40
		1.5 ft. Right Side	2	0/2/3/4	20
		1.5 ft. Left Side	2	4	0
		2.5 ft. Straight	2	1/4/5	0
		2.5 ft. Right Side	2	2/4	40
		2.5 ft. Left Side	2	4/5	0
		3.5 ft. Straight	2	1/2/3/4	10
		3.5 ft. Right Side	2	2/3/4	30
		3.5 ft. Left Side	2	4	0
Person 2:	Trial 1:	Position	Expected Prediction Results	Actual Prediction Results	Prediction Rate (%) False Positives Rate (%)
		1.5 ft. Straight	1	1/4/5	30
		1.5 ft. Right Side	1	0/3/4/5	0
		1.5 ft. Left Side	1	-	-
		2.5 ft. Straight	1	3/4	0
		2.5 ft. Right Side	1	0/3/5	0

Trial 2:	2.5 ft. Left Side	1	-	-	100
	3.5 ft. Straight	1	2/3/4/5	0	0
	3.5 ft. Right Side	1	0/1/4/5	25	20
	3.5 ft. Left Side	1	1/4/5	20	10
	1.5 ft. Straight	1	1/4/5	10	0
	1.5 ft. Right Side	1	0/5	0	0
	1.5 ft. Left Side	1	1/3/4	10	10
	2.5 ft. Straight	1	0/3/5	0	0
	2.5 ft. Right Side	1	0/5	0	10
	2.5 ft. Left Side	1	0/1/4	50	0
	3.5 ft. Straight	1	3	0	0
	3.5 ft. Right Side	1	1/4/5	10	0
	3.5 ft. Left Side	1	1/4/5	50	10
Trial 3:	1.5 ft. Straight	1	0/3/5	0	10
	1.5 ft. Right Side	1	1/4/5	40	0
	1.5 ft. Left Side	1	1/4	50	20
	2.5 ft. Straight	1	0/2	0	0
	2.5 ft. Right Side	1	0/1/4	50	10
	2.5 ft. Left Side	1	1/4/5	15	20
	3.5 ft. Straight	1	0/1/3/4/5	25	10
	3.5 ft. Right Side	1	1/3/5	20	5
	3.5 ft. Left Side	1	1/4	50	10

Person 3:	Trial 1:	Position	Expected Prediction Results	Actual Prediction Results	Prediction Rate (%)	False Positives Rate (%)
		1.5 ft. Straight	8	0/1/5	30	20
		1.5 ft. Right Side	8	1/2/5	50	0
		1.5 ft. Left Side	8	3/4	0	60
		2.5 ft. Straight	8	0/2/3	0	20
		2.5 ft. Right Side	8	0/2/5	60	10
		2.5 ft. Left Side	8	1/3/4/5	25	0
		3.5 ft. Straight	8	3	0	0
		3.5 ft. Right Side	8	0/2	0	0
		3.5 ft. Left Side	8	3/4	0	0
	Trial 2:	1.5 ft. Straight	8	2/5	90	15
		1.5 ft. Right Side	8	0/1/5	30	10
		1.5 ft. Left Side	8	1/4	0	100
		2.5 ft. Straight	8	1/2	0	10

Trial 3:	2.5 ft. Right Side	8	0/2/5	30	5
	2.5 ft. Left Side	8	3/4	0	0
	3.5 ft. Straight	8	2/5	75	10
	3.5 ft. Right Side	8	1/2/4/5	25	5
	3.5 ft. Left Side	8	1/3/4/5	20	5
	1.5 ft. Straight	8	0/2	0	30
	1.5 ft. Right Side	8	1/2	0	20
	1.5 ft. Left Side	8	1/7	0	80
	2.5 ft. Straight	8	0/1/3	0	20
	2.5 ft. Right Side	8	2/3/5	50	10
	2.5 ft. Left Side	8	3/4	0	0
	3.5 ft. Straight	8	0/1/5	50	5
	3.5 ft. Right Side	8	1/2/5	75	5
	3.5 ft. Left Side	8	4	0	10

Person 4:	Trial 1:	Position	Expected Prediction Results	Actual Prediction Results	Prediction Rate (%)	False Positives Rate (%)
	Trial 2:	1.5 ft. Straight	0	0/2/3	25	0
		1.5 ft. Right Side	0	2/4	0	0
		1.5 ft. Left Side	0	0/1/2	50	0
		2.5 ft. Straight	0	0/2/3	50	10
		2.5 ft. Right Side	0	2/3/4	0	0
		2.5 ft. Left Side	0	0/2/5	50	100
		3.5 ft. Straight	0	0/2/5	20	0
		3.5 ft. Right Side	0	0/2/3	15	5
		3.5 ft. Left Side	0	0/1	60	5
		1.5 ft. Straight	0	0/3/5	60	100
		1.5 ft. Right Side	0	2/3/4	0	50
		1.5 ft. Left Side	0	1/2/5	0	100
	Trial 3:	2.5 ft. Straight	0	0/2/3	50	0
		2.5 ft. Right Side	0	2/3/4	0	10
		2.5 ft. Left Side	0	1/3/5	0	50
		3.5 ft. Straight	0	0/1/2/3	50	0
		3.5 ft. Right Side	0	2/3/4	0	0
		3.5 ft. Left Side	0	0/1/2/4	75	0
		1.5 ft. Straight	0	0/2/3	15	10
		1.5 ft. Right Side	0	0/3/4	60	20

1.5 ft. Left Side	0	0/2	50	80
2.5 ft. Straight	0	2/3	0	5
2.5 ft. Right	0	2/3/4	0	20
Side	0	0/3	60	100
2.5 ft. Left Side	0	1/2/5	0	0
3.5 ft. Straight	0	0/2/3/4	30	0
3.5 ft. Right	0	1/2	0	30
Side	0			
3.5 ft. Left Side	0			

APPENDIX E
1:1 EIGENFACES RESULTS

Eigenface						
Person 1:	Trial 1:	Position	Expected Prediction Results	Actual Prediction Results	Prediction Rate (%)	False Positives Rate (%)
		1.5 ft. Straight	2	2	100	20
		1.5 ft. Right Side	2	2	100	60
		1.5 ft. Left Side	2	2	40	30
		2.5 ft. Straight	2	2	100	70
		2.5 ft. Right Side	2	2	70	100
		2.5 ft. Left Side	2	2	10	80
		3.5 ft. Straight	2	2	100	20
		3.5 ft. Right Side	2	2	100	10
		3.5 ft. Left Side	2	2	10	70
	Trial 2:	1.5 ft. Straight	2	2	100	80
		1.5 ft. Right Side	2	2	95	10
		1.5 ft. Left Side	2	2	10	50
		2.5 ft. Straight	2	2	100	40
		2.5 ft. Right Side	2	2	100	60
		2.5 ft. Left Side	2	2	30	40
		3.5 ft. Straight	2	2	100	100
		3.5 ft. Right Side	2	2	90	10
		3.5 ft. Left Side	2	2	95	10
	Trial 3:	1.5 ft. Straight	2	2	100	100
		1.5 ft. Right Side	2	2	100	20
		1.5 ft. Left Side	2	2	0	10
		2.5 ft. Straight	2	2	100	100
		2.5 ft. Right Side	2	2	95	100
		2.5 ft. Left Side	2	2	0	100
		3.5 ft. Straight	2	2	100	10
		3.5 ft. Right Side	2	2	100	10
		3.5 ft. Left Side	2	2	80	20

Person 2:	Trial 1:	Position	Expected Prediction Results	Actual Prediction Results	Prediction Rate (%)	False Positives Rate (%)
		1.5 ft. Straight	-	2	0	0
		1.5 ft. Right Side	-	2	0	0
		1.5 ft. Left Side	-	-	100	0

Trial 2:	2.5 ft. Straight	-	2	0	0
	2.5 ft. Right Side	-	2	0	0
	2.5 ft. Left Side	-	2	0	0
	3.5 ft. Straight	-	2	0	0
	3.5 ft. Right Side	-	2	0	100
	3.5 ft. Left Side	-	2	0	0
	1.5 ft. Straight	-	2	0	0
	1.5 ft. Right Side	-	2	0	20
	1.5 ft. Left Side	-	2	0	50
	2.5 ft. Straight	-	2	0	10
	2.5 ft. Right Side	-	2	0	10
	2.5 ft. Left Side	-	2	0	0
	3.5 ft. Straight	-	2	0	20
	3.5 ft. Right Side	-	2	0	20
	3.5 ft. Left Side	-	2	20	10
Trial 3:	1.5 ft. Straight	-	2	0	10
	1.5 ft. Right Side	-	2	0	10
	1.5 ft. Left Side	-	2	0	10
	2.5 ft. Straight	-	2	0	0
	2.5 ft. Right Side	-	2	50	0
	2.5 ft. Left Side	-	2	100	10
	3.5 ft. Straight	-	2	0	0
	3.5 ft. Right Side	-	2	0	20
	3.5 ft. Left Side	-	2	0	10

Person 3:	Trial 1:	Position	Expected Prediction Results	Actual Prediction Results	Prediction Rate (%)	False Positives Rate (%)
		1.5 ft. Straight	-	2	0	10
		1.5 ft. Right Side	-	-	100	0
		1.5 ft. Left Side	-	-/2	50	80
		2.5 ft. Straight	-	2	0	0
		2.5 ft. Right Side	-	-	100	0
		2.5 ft. Left Side	-	-	100	20
		3.5 ft. Straight	-	2	0	0
		3.5 ft. Right Side	-	-	100	20
		3.5 ft. Left Side	-	-	100	100

Trial 2:	1.5 ft. Straight	-	2	0	20
	1.5 ft. Right Side	-	-	100	20
	1.5 ft. Left Side	-	-	100	30
	2.5 ft. Straight	-	2	0	0
	2.5 ft. Right Side	-	-	100	0
	2.5 ft. Left Side	-	2	0	25
	3.5 ft. Straight	-	2	0	10
	3.5 ft. Right Side	-	-	0	10
	3.5 ft. Left Side	-	-/2	75	20
Trial 3:	1.5 ft. Straight	-	2	0	0
	1.5 ft. Right Side	-	-	100	10
	1.5 ft. Left Side	-	-/2	25	20
	2.5 ft. Straight	-	2	0	0
	2.5 ft. Right Side	-	-	100	0
	2.5 ft. Left Side	-	-/2	50	80
	3.5 ft. Straight	-	2	0	0
	3.5 ft. Right Side	-	-	100	0
	3.5 ft. Left Side	-	-	100	80

APPENDIX F

1:1 LOCAL BINARY PATTERN (ORIGINAL) RESULTS

Local Binary Pattern Histogram (Original)						
Person 1:	Trial 1:	Position	Expected Prediction Results	Actual Prediction Results	Prediction Rate (%)	False Positives Rate (%)
	Trial 1:	1.5 ft. Straight	2	2	100	5
		1.5 ft. Right Side	2	2	100	0
		1.5 ft. Left Side	2	2	100	0
		2.5 ft. Straight	2	2	100	100
		2.5 ft. Right Side	2	2	100	100
		2.5 ft. Left Side	2	2	100	70
		3.5 ft. Straight	2	2	100	80
		3.5 ft. Right Side	2	2	100	20
		3.5 ft. Left Side	2	2	100	80
	Trial 2:	1.5 ft. Straight	2	2	100	20
		1.5 ft. Right Side	2	2	100	5
		1.5 ft. Left Side	2	2	20	90
		2.5 ft. Straight	2	2	100	20
		2.5 ft. Right Side	2	2	100	80
		2.5 ft. Left Side	2	2	100	10
		3.5 ft. Straight	2	2	100	100
		3.5 ft. Right Side	2	2	100	20
		3.5 ft. Left Side	2	2	100	100
	Trial 3:	1.5 ft. Straight	2	2	100	0
		1.5 ft. Right Side	2	2	100	10
		1.5 ft. Left Side	2	2	80	80
		2.5 ft. Straight	2	2	100	70
		2.5 ft. Right Side	2	2	100	80
		2.5 ft. Left Side	2	2	100	10
3.5 ft. Straight		2	2	100	30	
3.5 ft. Right Side		2	2	100	70	
3.5 ft. Left Side		2	2	100	50	

Person 2:	Trial 1:	Position	Expected Prediction Results	Actual Prediction Results	Prediction Rate (%)	False Positives Rate (%)
		1.5 ft. Straight	-	2	0	100
		1.5 ft. Right Side	-	2	0	5
		1.5 ft. Left Side	-	2	0	20

Trial 2:	2.5 ft. Straight	-	2	0	0
	2.5 ft. Right Side	-	2	0	20
	2.5 ft. Left Side	-	2	0	0
	3.5 ft. Straight	-	2	0	0
	3.5 ft. Right Side	-	2	0	0
	3.5 ft. Left Side	-	2	0	0
				0	
	1.5 ft. Straight	-	2	0	0
	1.5 ft. Right Side	-	2	0	0
	1.5 ft. Left Side	-	2	10	20
	2.5 ft. Straight	-	2	0	0
	2.5 ft. Right Side	-	2	0	0
	2.5 ft. Left Side	-	2	0	0
	3.5 ft. Straight	-	2	0	0
	3.5 ft. Right Side	-	2	0	0
	3.5 ft. Left Side	-	2	0	10
Trial 3:	1.5 ft. Straight	-	2	0	0
	1.5 ft. Right Side	-	2	0	0
	1.5 ft. Left Side	-	2	0	0
	2.5 ft. Straight	-	2	0	0
	2.5 ft. Right Side	-	2	0	0
	2.5 ft. Left Side	-	2	0	0
	3.5 ft. Straight	-	2	0	0
	3.5 ft. Right Side	-	2	0	0
	3.5 ft. Left Side	-	2	30	0

Person 3:	Trial 1:	Position	Expected Prediction Results	Actual Prediction Results	Prediction Rate (%)	False Positives Rate (%)
		1.5 ft. Straight	-	2	0	0
		1.5 ft. Right Side	-	-	100	25
		1.5 ft. Left Side	-	-/2	50	50
		2.5 ft. Straight	-	2	0	20
		2.5 ft. Right Side	-	-	100	25
		2.5 ft. Left Side	-	-/2	50	20
		3.5 ft. Straight	-	2	0	0
		3.5 ft. Right Side	-	2	0	0
		3.5 ft. Left Side	-	2	0	0

Trial 2:	1.5 ft. Straight	-	2	0	10
	1.5 ft. Right Side	-	-	100	0
	1.5 ft. Left Side	-	-	100	80
	2.5 ft. Straight	-	2	0	0
	2.5 ft. Right Side	-	-/2	20	10
	2.5 ft. Left Side	-	2	0	0
	3.5 ft. Straight	-	2	0	0
	3.5 ft. Right Side	-	-/2	50	0
	3.5 ft. Left Side	-	-/2	50	20
Trial 3:	1.5 ft. Straight	-	2	0	0
	1.5 ft. Right Side	-	-	100	100
	1.5 ft. Left Side	-	-	100	100
	2.5 ft. Straight	-	2	0	0
	2.5 ft. Right Side	-	-	100	10
	2.5 ft. Left Side	-	-	100	100
	3.5 ft. Straight	-	2	0	0
	3.5 ft. Right Side	-	-	100	0
	3.5 ft. Left Side	-	-	100	100

APPENDIX G

1:1 LOCAL BINARY PATTERN (MODIFIED) RESULTS

Local Binary Pattern Histogram (Modified)						
Person 1:	Trial 1:	Position	Expected Prediction Results	Actual Prediction Results	Prediction Rate (%)	False Positives Rate (%)
		1.5 ft. Straight	2	2	100	5
		1.5 ft. Right Side	2	2	100	0
		1.5 ft. Left Side	2	2	100	0
		2.5 ft. Straight	2	2	100	0
		2.5 ft. Right Side	2	2	100	80
		2.5 ft. Left Side	2	2	100	20
		3.5 ft. Straight	2	2	100	20
		3.5 ft. Right Side	2	2	100	20
		3.5 ft. Left Side	2	2	60	30
	Trial 2:	1.5 ft. Straight	2	2	100	100
		1.5 ft. Right Side	2	2	10	60
		1.5 ft. Left Side	2	2	100	60
		2.5 ft. Straight	2	2	100	95
		2.5 ft. Right Side	2	2	100	20
		2.5 ft. Left Side	2	2	100	90
		3.5 ft. Straight	2	2	100	90
		3.5 ft. Right Side	2	2	80	80
		3.5 ft. Left Side	2	2	95	10
	Trial 3:	1.5 ft. Straight	2	2	100	100
		1.5 ft. Right Side	2	2	100	100
		1.5 ft. Left Side	2	2	95	70
		2.5 ft. Straight	2	2	100	95
		2.5 ft. Right Side	2	2	100	100
		2.5 ft. Left Side	2	2	70	90
		3.5 ft. Straight	2	2	100	5
		3.5 ft. Right Side	2	2	100	70
		3.5 ft. Left Side	2	2	100	95

Person 2:	Trial 1:	Position	Expected Prediction Results	Actual Prediction Results	Prediction Rate (%)	False Positives Rate (%)
		1.5 ft. Straight	-	2	0	0
		1.5 ft. Right Side	-	2	0	20
		1.5 ft. Left Side	-	2	20	50

Trial 2:	2.5 ft. Straight	-	2	0	0
	2.5 ft. Right Side	-	2	20	0
	2.5 ft. Left Side	-	2	0	0
	3.5 ft. Straight	-	2	0	0
	3.5 ft. Right Side	-	2	0	0
	3.5 ft. Left Side	-	2	0	0
	1.5 ft. Straight	-	2	0	0
	1.5 ft. Right Side	-	2	0	0
	1.5 ft. Left Side	-	2	0	0
	2.5 ft. Straight	-	2	0	0
	2.5 ft. Right Side	-	2	0	10
	2.5 ft. Left Side	-	2	0	10
Trial 3:	3.5 ft. Straight	-	2	0	10
	3.5 ft. Right Side	-	2	0	0
	3.5 ft. Left Side	-	2	0	0
	1.5 ft. Straight	-	2	0	0
	1.5 ft. Right Side	-	2	0	0
	1.5 ft. Left Side	-	2	0	0
	2.5 ft. Straight	-	2	0	0
	2.5 ft. Right Side	-	2	0	0
	2.5 ft. Left Side	-	2	0	0
	3.5 ft. Straight	-	2	0	0
	3.5 ft. Right Side	-	2	0	5
	3.5 ft. Left Side	-	2	0	0

Person 3:	Trial 1:	Position	Expected Prediction Results	Actual Prediction Results	Prediction Rate (%)	False Positives Rate (%)
		1.5 ft. Straight	-	2	0	0
		1.5 ft. Right Side	-	-	100	20
		1.5 ft. Left Side	-	-/2	25	100
		2.5 ft. Straight	-	2	0	0
		2.5 ft. Right Side	-	-	100	30
		2.5 ft. Left Side	-	-/2	25	85
		3.5 ft. Straight	-	2	0	0
		3.5 ft. Right Side	-	-	100	0
		3.5 ft. Left Side	-	-/2	50	0

Trial 2:	1.5 ft. Straight	-	2	0	0
	1.5 ft. Right Side	-	-/2	75	20
	1.5 ft. Left Side	-	2	0	80
	2.5 ft. Straight	-	2	0	0
	2.5 ft. Right Side	-	-	100	50
	2.5 ft. Left Side	-	2	0	20
	3.5 ft. Straight	-	2	0	10
	3.5 ft. Right Side	-	-	100	20
	3.5 ft. Left Side	-	2	0	80
Trial 3:	1.5 ft. Straight	-	2	0	10
	1.5 ft. Right Side	-	-/2	25	0
	1.5 ft. Left Side	-	-/2	10	10
	2.5 ft. Straight	-	2	0	0
	2.5 ft. Right Side	-	-/2	75	10
	2.5 ft. Left Side	-	2	0	0
	3.5 ft. Straight	-	2	0	10
	3.5 ft. Right Side	-	-	100	10
	3.5 ft. Left Side	-	2	0	0

REFERENCES

- [1] Michael L. Rich, Machine Learning, "Automated Suspicion Algorithms, and the Fourth Amendment," *University of Pennsylvania Law Review*, vol. 164, pp. 871-929, 2016.
- [2] Rabia Jafri and Hamid R. Arabnia, "A Survey of Face Recognition Techniques," *Journal of Information Processing Systems*, vol. 5, no. 2, pp. 41-68, June 2009.
- [3] Andrea F. Abate et al, "2D and 3D face recognition: A survey," *Science Direct: Pattern Recognition Letters*, vol. 28, pp. 1885-1906, January 2007.
- [4] Matthew A. Turk and Alex P. Pentland. "Face Recognition Using Eigenfaces," presented at the 1991 IEEE Computer Society Conference on Computer Vision and Pattern Recognition, June 3-6, 1991, pp. 586-591.
- [5] Md. Abdur Rahim et al, "Face Recognition using Local Binary Patterns (LBP)," *Global Journal of Computer Science and Technology Graphics & Vision*, vol. 13, no. 4, pp. 1-8, 2013.
- [6] C. G. Tredoux et al., "Face Reconstruction using a Configural, Eigenface-based Composite System," *3rd Biennial Meeting of the Society for Applied Research in Memory and Cognition (SARMAC)*. Boulder, Colorado, USA, 1999.
- [7] CNN, "Education School Face Scanner to Search for Sex Offenders," Phoenix, Arizona: *The Associated Press*, 2003.

- [8] D. McCullagh, "Call It Super Bowl Face Scan 1," *Wired Magazine*, 2001.
- [9] E. Acosta et al, "An Automatic Face Detection and Recognition System for Video Indexing Applications," *Proceedings of the IEEE International Conference on Acoustics, Speech and Signal Processing*, Vol.4. Orlando, Florida, 2002, pp.3644-3647.
- [10] Fatma Zohra Chelali and Amar Djeradi, "CSLBP and OCLBP Local Descriptors for Speaker Identification from Video Sequences," in *Third World Conference on Complex Systems (WCCS) 2015*, 2015.
- [11] H. Moon, "Biometrics Person Authentication Using Projection-Based Face Recognition System in Verification Scenario," *International Conference on Bioinformatics and its Applications*, Hong Kong, China, 2004, pp.207-213.
- [12] J.-H. Lee and W.-Y. Kim, "Video Summarization and Retrieval System Using Face Recognition and MPEG-7 Descriptors," *Image and Video Retrieval*, Vol.3115, Lecture Notes in Computer Science: Springer Berlin / Heidelberg, 2004, pp.179-188.
- [13] J. N. K. Liu et al, "iBotGuard: An Internet-Based Intelligent Robot Security System Using Invariant Face Recognition Against Intruder," *IEEE Transactions on Systems Man And Cybernetics Part C-Applications And Reviews*, Vol.35, pp.97-105, 2005.

- [14] K. Kim, "Intelligent Immigration Control System by Using Passport Recognition and Face Verification," *International Symposium on Neural Networks*. Chongqing, China, 2005, pp.147-156.
- [15] Li Liu, Lingjun Zhao et al, "Extended Local Binary Patterns for Texture Classification," *Image and Vision Computing*, Vol.30, no.2, pp. 86-99, February 2012.
- [16] Li Liu, Songyang Lao et al, "Median Robust Extended Local Binary Pattern for Texture Classification," Vol.25, pp. 1368-1381, March 2016.
- [17] P. J. Phillips et al, "The FERET Evaluation Methodology for Face Recognition Algorithms," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, Vol.22, pp.1090-1104, 2000.
- [18] Peter N. Belhumeur et al, "Eigenfaces vs Fisherfaces: Recognition Using Class Specific Linear Projection," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, Vol. 19, no.7, pp. 711-720, July 1997.
- [19] Rob Schapire, "Theoretical Machine Learning,"
<http://www.cs.princeton.edu/courses/archive/spr08/cos511/>, February 2008.
- [20] S. L. Wijaya et al, "Illumination-Tolerant Face Verification of Low-Bitrate JPEG2000 Wavelet Images with Advanced Correlation Filters for Handheld Devices," *Applied Optics*, Vol.44, pp.655-665, 2005.

- [21] T. Choudhry et al, "Multimodal Person Recognition Using Unconstrained Audio and Video," Proceedings, International Conference on Audio and Video-Based Person Authentication, 1999, pp.176-181.
- [22] Timo Ahonen et al, "Face Description with Local Binary Patterns: Application to Face Recognition," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, Vol.28 no.12, pp. 2037-2041, December 2006.
- [23] Xiaofeng Fu and Wei Wei, "Centralized Binary Patterns Embedded with Image Euclidean Distance for Facial Expression Recognition," in *Proc. International Conference on Natural Computation*, Vol. 4, pp. 115-119, 2008.