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Face Recognition at a Distance Using Average Pixel Super Resolution

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Declaration: I Certify that this thesis submitted for the Degree of Master is the result of my own research, except where otherwise acknowledged, and that this thesis (or any part of the same) has not been submitted for a higher degree to any other university or institution.

Signed: ....

Rasha Derar Ali Saffarini

Date: 28, January, 2017

Dedication

I dedicate this work to my family especially my parent who always supported me, and my brother who stayed beside me, gave me all the help I needed, encourages me step by step.

Rasha Derar Ali Saffarini

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As I am writing the last words of this thesis, I greatly appreciate the thesis supervisor Dr. Salah Eldeen Odeh for his support and his time that he spent with me in order to make this thesis successful one.

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Abstract

This research is aimed to improve the performance of face recognition with Low Resolution (LR) images through proposing anew image enhancement algorithm which called Average-Pixel Super Resolution (APSR). APSR finds the distance between LR images and their correspondent HR images, taking averages of pixel's values to finally construct a HR image from LR image that is close to original HR images in the database of the same person. This approach was evaluated and the experiments were

conducted using training and testing images from COLOR FERET database. Experiments, results showed that the performance is approximately 30% better than using traditional face recognition algorithms with LR images without construct HR image from LR image.

التعرف على الوجوه باستخدام خوارزمية Average Pixel Super Resolution

إعداد : رشا ضرار علي سفاريني

إشراف : د. صلاح الدين عودة

ملخص :

يهدف البحث الى تحسين اداء انظمة التعرف على الوجوه عن بعد عن طريق العمل على تطوير خوارزمية تسمى Average . pixel super resolution بهدف التعرف على الشخص الموجود فيها, حيث بالاعتماد على قيمة الفرق المحسوب نقوم بعمل تحسين للصورة قليلة الدقة عن طريق بناء صورة جديدة ذات وضوح اكبر من الصورة قليلة الدقة بحيث تكون الصورة الجدية ذات دقة قريبة من دقة الصور الموجودة في قاعدة البيانات .تم فحص الخوارزمية عن طريق عقد لعديد من التجارب باستخدام قاعدة البيانات المسماة COLOR FERET database اظهرت نتائج التجارب ان الاداء بالتعرف على الوجوه افضل بنسبة ما يقارب ٣٠٪ من محاولة التعرف على الوجوه دون استخدام الخوارزمية و تحسين الصورة الماخوذة.

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List of MATLAB functions

Function name	Description
Zeroes()	Used to create zeroes matrix
Size()	Used to return the size of specified matrix
Mean()	Used to find the average of specified matrix
webcam()	Used to open and start the camera
Imcrop()	Used to cut a specific region (which is the detected face) from an image
Vision.cascadeobjectdetector()	Used to create object called face detector to find the face from a specific image
Step(image, facedetector)	Used to return the coordinates of the face in the image
Rgbtogray()	Used to convert RGB colored image to gray image
Snapshot()	Used to take image from the camera

List of Abbreviations

PCA	Principal Component Analysis
DWT	Discrete Wavelet Transform
LL sub band	Low-Low sub band
SVM	Support Vector Machine
NNC	Nearest Neighbor Classifier
FRAD	Face Recognition At a Distance
DCT	Discrete Cosine Transform
GMM	Gaussian Mixture Model
MAP estimation	maximum a posteriori probability
FERET database	Facial Recognition Technology

Chapter 1: Introduction

The chapter provides an introduction about face recognition in general, its stages, and brief description about each stage, also it describes the problem we want to solve to be aware of what the problem we face and the solution we aim to propose.

1.1. Face Recognition

Recently face recognition is attracting much attention in the society of network multimedia information access. The aim of face recognition systems is to automatically identify or verify a specific person. Commercial face recognition applications have been popular in the fields of access control, security and surveillance systems, as well as bio-metrics and law enforcement. Some facial recognition software uses algorithms that analyze specific facial features, such as the relative position, size and shape of a person's nose, eyes, jaw and cheekbones. One of the ways to do this is by comparing value of face calculated from the face image and values of facial database [1].

All face recognition algorithms use databases that contain facial images of many persons in different poses, it has nearly 10 photos of each person, some of them is used for training, the others are used for testing. Figure 1.1 shows example of facial database [2].

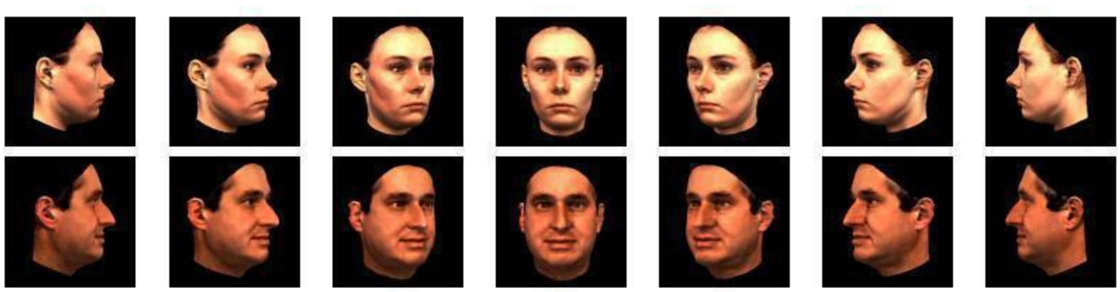


Figure 1.1: Facial database [2]

In general, face recognition algorithms go through 4 stages: face detection, analysis, comparison, recognition, where each phase of them is divided into multiple steps. These stages are shown in Figure 1.2:

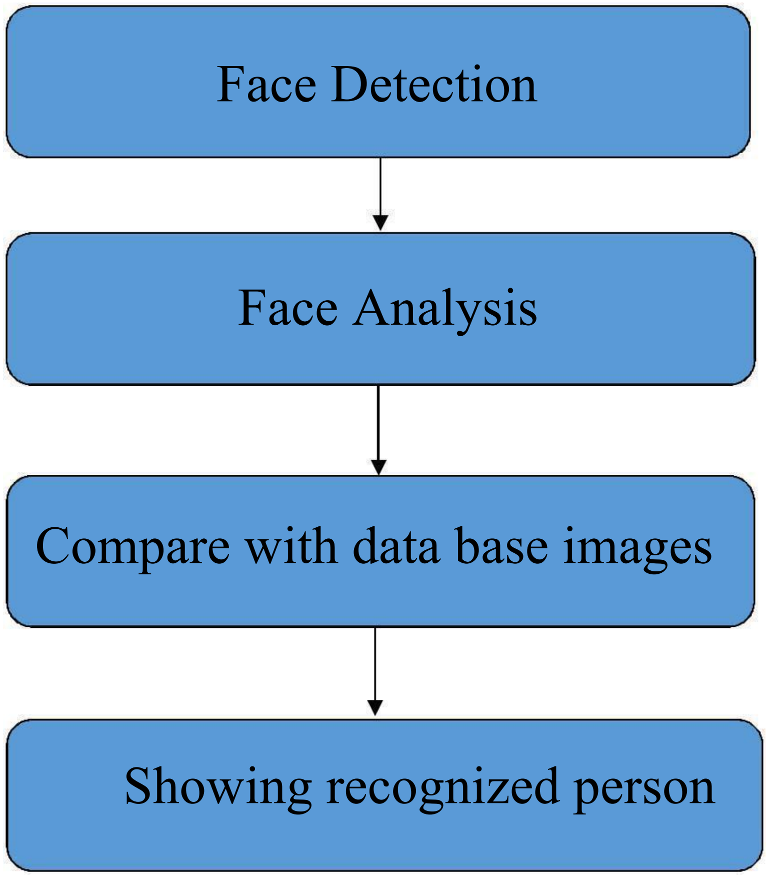


Figure 1.2: Face recognition steps.

- Face detection: This phase includes only the process of detecting the face region from the whole input image in order to enter it to the next phase for the purpose of analyzing it.
- Face Analysis: Images from the first stage is operated here and analyzed to extract information from it; that information is used to compute some values that will be used later in the comparison stage.

- Compare with the database: after applying the previous stage on all images in the database, it will be applied also on the test image. At the end, we will have a value correspondent to each image, where each value produced from test image is compared with all values produced from database images to find the most matched value.

- Show the recognized person: after comparing the achieved value from testing the image with all values from the database images, we will find the closest value using a threshold value to find the searched person and display his name.

1.2. Problem statement

For near distance face recognition, the images captured by the camera will be of high resolution and have clear face images, but in the approach of face recognition at a distance (FRAD), the clarity and quality of face images become a big issue, meaning that the face recognition rate is steady when using high resolution (HR) images. Oppositely, when the resolution decreases, the recognition rate is obviously affected and goes down, because with lower resolution some of the information is lost.

1.3. Purpose of the research:

The aim of our research is to develop a super resolution face recognition method which is superior compared to other face recognition approaches, as well as can be used for improving the low resolution face recognition performance. The approach proposed is designated as Average-Pixel Super Resolution (APSR). The APSR approach is developed using Matlab to find distance between low resolution images and their correspondent HR images, taking the averages of pixel's values to finally construct HR image from LR image that is close to original HR images stored in the database for the same person.

1.4. Outline

The content of this thesis is arranged as follows:

Chapter 2: Literature review. In this chapter we introduce recognition, its types generally, also specifically we introduce face recognition and its methods, and finally we described some of super resolution methods.

Chapter 3: Algorithms. In this chapter, we discuss our method that is proposed to solve the problem of face recognition at a distance (FRAD).

Chapter 4: Experiments. This chapter includes a brief description about the database used in our experiments, in addition to all conducted experiments. The produced results in comparison with the related algorithms and the evaluation are discussed here.

Chapter 5: Conclusion. A conclusion of all work done is given in this chapter.

Chapter 2: Literature Review

This chapter provides an introduction to image processing in general and digital image processing in particular, after that we focused on a specific field of image processing which is recognition and its types, we then concentrate on one aspect of recognition which is called face recognition, especially face recognition at a distance (recognize persons from far distances), its problems and some of existing approaches used to solve those problems are discussed here.

2.1. Image processing

Image processing is the study of any algorithm that are developed for enhancing images obtained from cameras/sensors placed on satellites space probes and air crafts or pictures taken in normal day to day life for various applications and returns an image as output. Image processing includes: Image display and printing, image editing and manipulation, image enhancement, feature detection, image compression. Image Processing systems are becoming popular due to easy availability of powerful personnel computers, large size memory devices, graphics softwares etc. Moreover, it encompasses processes that extract attributes from images, up to and including the recognition of individual objects [4] [5].

2.2 Digital Image Processing:

Processing of digital images using a computer. In this case, computers are used to process the image. The image will be converted into digital information and then processing it. It is defined as subjecting numerical representations of objects to a series of operations in order to obtain a desired result. It starts with one image and produces a modified version. It is therefore a process that takes an image into another. The term digital image processing generally refers to processing of a two-dimensional picture by a digital computer.

An image is an array, or a matrix, of pixels (picture elements) arranged in columns and rows. In a (8-bit) gray scale image each picture element has an assigned intensity that ranges from 0 to 255. A gray scale image is what people normally call a black and white image, but the name emphasizes that such an image will also include many shades of gray. A normal gray scale image has 8 bit color depth = 256 gray scales. A "true color" image has 24 bit color depth $=2^8 \times 2^8 \times 2^8$ bits = 256 x 256 x 256 colors = ~16 million color= 2^{24}.

There are two general groups of 'images': vector graphics (or line art) and bitmaps (pixel-based or 'images'). Some of the most common file formats are [6]:

1. GIF — an 8-bit (256 color), non-destructively compressed bitmap format. Mostly it is used for web and has several sub-standards one of which is the animated GIF.

2. JPEG — a very efficient (i.e. much information per byte) destructively compressed 24 bit (16 million colors) bitmap format. Widely used, especially for Web and Internet (bandwidth-limited).

3. PS — Postscript, a standard vector format. It has numerous sub-standards and can be difficult to transport across platforms and operating systems.
4. PSD – a dedicated Photo-shop format that keeps all the information in an image including all the layers.
5. TIFF (Tagged Image File Format): stands for "Tagged Image File Format" and is a computer file format for storing raster graphics images (A bitmap, a single-bit raster, corresponds bit-for-bit with an image displayed on a screen, generally in the same format used for storage in the display's video memory, or maybe as a device-independent bitmap. A raster is technically characterized by the width and height of the image in pixels and by the number of bits per pixel or color depth, which determines the number of colors it can represent). it is standard in the printing, publishing industry, faxing, word processing, optical character recognition and other applications.

The principle advantage of Digital Image Processing methods is its versatility, repeatability and the preservation of original data precision [3].

2.3. Recognition

It is an aspect of computer vision that analyzes pictures and videos in order to identify something as having been previously seen, heard, or known. It is also defined as the identification of a thing or a person from previous encounters or knowledge, as it done by human senses.

Recognition fields:

- **Linguistic**

Natural language processing: In natural language processing, language identification or language guessing is the problem of determining which natural language the given content is in [4].

Speech recognition: Speech is the primary means of communication between people.

Speech recognition is the ability to recognize spoken words only and not the individual voice characteristics [7]. For reasons ranging from technological curiosity about the mechanisms for mechanical realization of human speech capabilities, to the desire to automate simple tasks inherently requiring human-machine interactions,

- **Textual**

Handwriting recognition: It provides a way of identifying the writer of a piece of handwriting in order to verify the claimed identity in security and related applications. It requires the writer to write the same fixed text. In this sense, signature verification may also be called text-dependent writer verification (which is a special case of text-dependent writer identification where more than one writer has to be considered) [8].

Magnetic inc character recognition: (MICR Code) is a character-recognition technology used mainly by the banking industry to ease the processing and clearance of cheques and other documents. The MICR encoding is called the MICR line, and can be found the bottom of cheques and other vouchers. It typically includes the document-type indicator, bank code, bank account number, cheque number, cheque amount, and a control indicator. [9].

Optical character recognition (OCR): is an important research area in pattern recognition. The objective of an OCR system is to recognize alphabetic letters, numbers, or other characters, which are in the form of digital images, without any human intervention [10]. This is accomplished by searching a match between the features extracted from the given character's image and the library of image models. Ideally, we would like the features to be distinct for different character images so that the computer can extract the correct model from the library without any confusion. At the same time, we also want the features to be robust enough in such a way that they will not be affected by viewing transformations, noises, resolution variations and other factors.

- **Bio-metric :**

Bio-metrics refers to technologies for measuring and analyzing persons physiologic or behavioral characteristics, these characteristics are unique that we can identify person using them. These techniques are useful because other security techniques like passwords or ID cards can be lost or forgotten or stolen or hacked [11].

Types of bio-metrics:

Finger print: refers to the automated method of verifying a match between two human fingerprints. Fingerprints are one of many forms of biometrics used to identify individuals and verify their identity. A capture device is used to take a graphical image of a fingerprint, typically captured as a TIFF (Tagged Image File Format) image. The graphical image obtained from the capture device is commonly referred to as a live scan to distinguish it from a template or print stored in a database. Processing software examines the fingerprint image and locates the image center, which may be off- center from the fingerprint core [12].

Iris: Iris recognition is an automated method of biometric identification that uses mathematical pattern-recognition techniques on video images of one or both of the irises of an individual's eyes, whose complex random patterns are unique, stable, and can be seen from some distance [13].

DNA: The cells that contain DNA share genetic material (information) through chromosomes. Humans have 23 chromosomes that house a person's DNA and their genes. Of the 46 total chromosomes, 23 come from each parent of an offspring. 99.7% of an offspring's DNA is shared with their parents. The remaining .3% of an individual DNA is variable repetitive coding unique to an individual. DNA recognition uses genetic profiling, also called genetic fingerprinting, to isolate and identify these repetitive DNA regions that are unique to each individual to either identify or verify a person's identity [14].

The basic steps of DNA profiling include [15]:

1)Isolate the DNA (sample can originate from blood, saliva, hair, semen, or tissue) 2) Section the DNA sample into shorter segments containing known variable number tandem repeats (VNTRs)—identical repeat sequences of DNA 3) Organize the DNA segments by size 4) Compare the DNA segments from various samples

Face Recognition: In the next section we will discuss face recognition in details.

2.4. Face recognition

Face recognition is one of the few biometric methods that possess the merits of both high accuracy and low accuracy. It has the accuracy of a physiological approach without being intrusive. Numerous algorithms were proposed for face recognition [16].

2.4.1 Some of face recognition algorithms

Many face recognition algorithms have been developed and each has its own strengths. In Principal Component analysis (PCA) method, also known as Eigen face method, face images are projected onto the Eigen space, that encodes the variations among the known facial classes and recognition is achieved by carrying out match of these projected feature vectors [17]. The Gram-Schmidt Orthogonalization based Face Recognition using Discrete Wavelet Transform (DWT) is presented in [21]. The DWT is applied on face images of Libor Spacek database. The Low-Low (LL) sub-band is considered and Fast Principal Component (PCA) Analysis using Gram-Schmidt Orthogonalization process is applied to generate feature coefficient vectors. Two feature extraction methods based on PCA and Wavelets on the ORL face database using support vector machine (SVM) and nearest neighbor classifier (NNC) is described in [22]. The prototype system in [23] built in lab finds facial match by utilizing multi algorithmic multi-biometric technique, combining gray level statistical correlation method with PCA or Discrete Cosine Transform techniques.

A Mufti-Manifold Discriminant Analysis method for image feature extraction and pattern recognition based on graph embedded learning and under the Fisher discriminant analysis framework is proposed in [20].

A comparison by using the average-half-face and the original full face is performed with 6 different algorithms applied to two-dimensional and three-dimensional databases [19]. The rank one accuracy of recognition is improved for average half face. A face detection method based on half face-template is discussed in [18].

display of statistical information that uses rectangles to show the frequency of data items in successive numerical intervals of equal size. Histogram modeling techniques (*e.g.* histogram equalization) provide a sophisticated method, which automatically minimizes the contrast in areas too light or too dark of an image [24].

2.4.2 Face recognition

On face recognition in general we work on facial images for face recognition techniques, in which we take an image from camera, analyzing it, search for it to find out whether the face of a specific person is in the database or not. Face recognition is divided into different stages as shown in figure 2.1 [25].

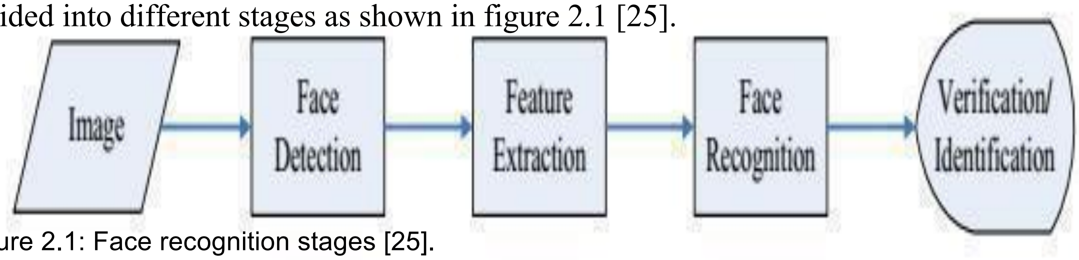


Figure 2.1: Face recognition stages [25].

The face recognition stages are:

- Face Detection: this is a required first step in face recognition systems. Face detection is the process of extracting faces from images. So, the system positively identifies a certain image region as a face [26]. A Web cam can be integrated into a computer and detect any face that walks by. The system then calculates the race, gender, and age range of the face. Once the information is collected, a series of advertisements can be played that is specific toward the detected race/gender/age.

- Feature extraction: After the face detection step, information is extracted from the image by taking information from each pixel in the image, face patches may be taken from different camera alignments, with different face expressions, illuminations, and may suffer from occlusion and clutter. To overcome these drawbacks, feature extractions are performed to do information packing, dimension reduction, salience extraction, and noise cleaning [25]. Output from this step is value, vector, or matrix of values used later for recognition.
- Face recognition: is the final step that comparing the values produced for the test image with those values produced for all images in the database to find the matched person.
- Verification/identification: in this stage the system displays the recognized person if a match is found.

2.4.4 Application of Face Recognition:

Face recognition is used in many aspects of life. Some of these fields are discussed as following: Access Control. Face verification, matching a face against a single enrolled exemplar, is well within the capabilities of current Personal Computer hardware. Increased ease-of-use over password protection is hard to argue with today's somewhat unreliable and unpredictable systems, and for few domains is there motivation to progress beyond the combinations of password and biometric security to increase the security level. Face verification is being used in kiosk applications, as cheque-cashing kiosk with no human supervision. The application domain where most interest in face recognition is being shown is probably surveillance. Video is the medium of choice for surveillance because of the richness and type of information that it contains and naturally, for applications that require identification, face recognition is the best biometric for video data, though gait or lip motion recognition have some potential. Face recognition can be applied without the subject's active participation, and indeed without the subject's knowledge. Automated face recognition can be applied 'live' to search for a watch-list of 'interesting' people, or after the fact using surveillance footage of a crime to search through a database of suspects [27,28]. The applications are listed in Table 1 [26]:

Areas	Applications
Information Security	Access security (OS, data bases) Data privacy (e.g. medical records) User authentication (trading, on line banking)
Access management	Secure access authentication (restricted facilities) Permission based systems Access log or audit trails
Biometrics	Person identification (national IDs, Passports, voter registrations, driver licenses) Automated identity verification (border controls)
Law Enforcement	Video surveillance Suspect identification Suspect tracking (investigation) Simulated aging Forensic Reconstruction of faces from remains
Personal security	Home video surveillance systems Expression interpretation (driver monitoring system)
Entertainment - Leisure	Home video game systems Photo camera applications

Table 1: Applications of face recognition [26].

2.5. Face Recognition at a Distance (FRAD)

Face recognition is the most popular bio-metric used in distance applications, which range from high security scenarios such as border control to others such as video games, but it is a challenging task because of the following reasons [29]:

1. It is hard to ensure the quality of the image
2. From a distance the hallucination and disruption in the image may be very high so it is hard to know the person
3. In the surveillance systems video camera is used and there is no cooperation from users to take photo of them.

2.5.1 Problems of FRAD

The main problems and some relevant solutions of FRAD are in [30]. Firstly, the images captured at a distance are usually with low resolution which will lead to low recognition accuracy. Using high-definition camera is a possible solution but it can result in decreasing the speed of detection. Secondly, interlace is a problem in video images. It happens when the faces are moving fast enough that each video frame is captured at a different position. A progressive scan video system can reduce the chance of interlace. Thirdly, in many cases of FRAD, the face is blurred because it is out of focus of the lens. The degree of blur can be decreased by small aperture lens. Fourthly, motion blur also happens frequently in FRAD when the face is moving fast or the camera is shaking. Rapid exposures can be used to avoid this problem, but the aperture stop would be increased which conflicts to the out-of-focus problem.

Furthermore, in FRAD especially under surveillance situation, it is also important to cover most users' heights and capture frontal faces. Besides, weather and atmospherics, such as thermal waves, have a significant impact on recognition accuracy [30]. Depending on the distance to the camera, face recognition could be applied in two different applications [19]: a) Requiring cooperative users (near distance), such as in entrance systems, b) Not requiring cooperative users (medium and far distances), such as face surveillance.

Depending on the previous discussion there are two scenarios of face recognition:

1- Close: that means the distance between user and camera is very low and needs cooperative of the user.

2- far: that the user is far from the camera and do not require cooperative users (medium and far distances), such as face surveillance.

In [29], faces are segmented and analyzed using VeriLook SDK. The results and errors of segmentation are listed in Table 2 [29].

	Close distance	**Medium distance**	**Far distance**	**discarded**	**Total**
Num. of images	**1468**	**836**	**660**	**360**	**3324**
Error	**21**	**151**	**545**		**848**
Error(%)	**1.43%**	**18.06%**	**82.57%**		

Table 2: face recognition scenarios results [29].

The errors increased in far distance because system can’t detect faces in far images, but they correct these errors by manually detect faces. Here in their work for face recognition, two recognition systems are used. One uses Principal Component Analysis (PCA) with (SVM) classifier; the other uses Discrete Cosine Transform (DCT) with (GMM) classifier.

2 Super Resolution:

The central aim of Super-Resolution (SR) is to generate a higher resolution image from lower resolution(LR) images. High resolution images give image with large pixel intensity, that is important in recognition and surveillance systems, but unfortunately the HR images are not available all the time, so we need to use super resolution algorithms to obtain them from low resolution images taken from a distance or taken by low quality camera [32]. This is illustrated in Figure 2.2:

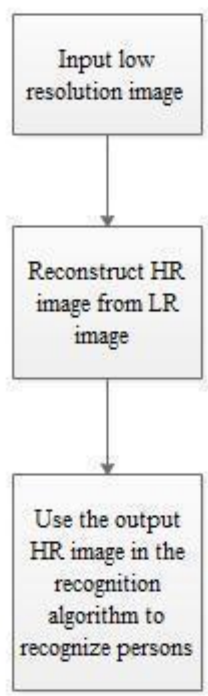


Figure 2.2: Super resolution steps in general.

2.5.3 Methods Used to Obtain SR From LR Images:

2.5.3.1 Low-Resolution Face Recognition Across Variations in Pose and Illumination

Prasad et al [33] proposed a completely automatic approach for recognizing low resolution face images captured in uncontrolled environment. The approach uses multidimensional scaling to learn a common transformation matrix for the entire face, which simultaneously transforms the facial features of the low resolution and the high resolution training images such that the distance between them approximates the distance had both the images been captured under the same controlled imaging conditions.

The approach performs quite well in matching faces across pose, illumination and resolution, but it requires the locations of several landmark locations (like corners of eyes, nose and mouth etc.). In the proposed approach, a common transformation matrix for the entire face region that can map both low resolution probe images and high resolution gallery images into a common space is learnt using multi-dimensional scaling method during training which is the Scale Invariant Feature Transform (SIFT). SIFT descriptors computed from the facial image are used as the descriptors of the face.

SIFT descriptors:

Image features have many properties that make them suitable for matching different images of an object or scene. The features are invariant to image scaling and rotation, and partially invariant to change in illumination and 3D camera viewpoint. Large numbers of features can be extracted from typical images with efficient algorithms.

For extracting these features, the following are the major stages of computation used to generate the set of image features [34]:

1. Scale-space extreme detection: The first stage of computation searches over all scales and image locations. It is implemented efficiently by using a difference-of-Gaussian function to identify potential interest points that are invariant to scale and orientation.
2. Key point localization: At each candidate location, a detailed model is fit to determine location and scale. Key points are selected based on measures of their stability.
3. Orientation assignment: One or more orientations are assigned to each key point location based on local image gradient directions. All future operations are performed on image data that has been transformed relative to the assigned orientation, scale, and location for each feature, thereby providing invariance to these transformations.
4. Key point descriptor: The local image gradients are measured at the selected scale in the region around each key point. These are transformed into a representation that allows for significant levels of local shape distortion and change in Illumination.

This approach has been named the Scale Invariant Feature Transform (SIFT), as it transforms image data into scale-invariant coordinates relative to local features. An important aspect of this approach is that it generates large numbers of features that densely cover the image over the full range of scales and locations. A typical image of size 500×500 pixels will give rise to about 2000 stable features (although this number depends on both image content and choices for various parameters). The quantity of features is particularly important for object recognition, where the ability to detect small objects in cluttered backgrounds requires that at least 3 features be correctly matched from each object for reliable identification. For image matching and recognition, SIFT features are first extracted from a set of reference images and stored in a database. A new image is matched by individually comparing each feature from the new image to this previous database and finding candidate matching features based on Euclidean distance of their feature vectors [34].

In this work, rootSIFT descriptors discussed in the previous paragraph are computed at 15 fiducial locations in the interior of the face as the face representation. Let the transform ***g*** be defined by ***g : Rn → Rd***, where ***n*** is the dimension of input feature vectors and ***d*** is the dimension of the transformed space. The mapping ***g = (g1, g2, · · · , gd) T*** can be expressed as a linear combination of k basis vectors as given below :

$$g_i(f; w) = \sum_{j=1}^{k} w_{ij}\psi_j(f) \tag{2.2}$$

where ***ψj*** (f); j = 1, 2, · · ·. k is a linear or non-linear function, where f is the input feature vector and W is the transformation matrix whose elements are to be computed.

Based on these observations, this algorithm is a modification of the reference-based approach. Using the reference-based approach, they obtain distances between the probe and the gallery images. Based on these distances, the top K gallery images are picked and direct stereo matching is performed between them and the probe image to obtain a better estimate of their distance leading to better accuracies at top ranks is set to 10 for this experiment. With this modification, the rank-1 accuracy improves from 55% to 80% at the expense of 10 extra stereo cost computations.

2.5.3.2 simultaneous super-resolution and recognition (S^2R^2)

In [35], an algorithm called simultaneous super-resolution and recognition (S^2R^2) is proposed. A high-resolution training set is needed and let F be the super-resolution feature which is provided by the training set. For an input low-resolution probe image ***Ip*** and the class k is claimed, first task is to solve the problem

$$x_p = \arg\min \ ||Bx - I_p \|^2 + \propto^2 \| Lx \|^2 + \beta^2 \ \| Fx - FI_g \|^2 \qquad (2.3)$$

where ***Ig*** is the gallery image with class ***k***. Matrix ***B*** is the linear model for down sampling the HR image ***x*** to its corresponding LR image ***Ip***. ***Lx*** is a vector of edge values in which ***L*** is first or second derivative approximation. ***α*** is a regularization parameter. ***β*** is an additional regularization parameter. Then the distance is measured by a combination of the residual norm on each set of model assumptions in Equation 2.3.

According to their experiment results, the performance of this algorithm is better than the original LR, bilinear interpolation, hallucinating faces and Tikhonov regulation. This method is also extended for multiple resolution problems that the training images and gallery images are with different resolution and can be applied to non-linear features by using an appropriate non-linear optimization algorithm to minimize Equation.

Furthermore, this method is improved in [36]. Nonetheless, this approach has to do optimization for every image in the gallery which requires long time especially for large database.

2.5.3.3 Face super-resolution reconstruction and recognition from Low-resolution image sequences

In the method presented in [37], a routine that uses both SR and Gabor wavelets to perform recognition on LR face image sequences is discussed. The proposed approach first constructs a HR face image by fully utilizing the sub-pixel information provided in the LR sequences, and then performs Gabor feature based recognition.

In SR image reconstruction, each LR frame contributes new information for interpolating sub-pixel values of the same scene. To get different information of the same scene, relative scene motions must be recorded from frame to frame. If these scene motions are known or can be estimated within sub-pixel accuracy, SR image reconstruction is possible. Each LR frame can be modeled as a noisy and down sampled version of the HR image that has been shifted and blurred, or more formally

$$y = wz + n \qquad (2.4)$$

where y is a $NM^2 \times 1$ vector representing N measured LR images of the same $M \times M$ size in lexicographic order, z is a $q^2M^2 \times 1$ vector representing the $qM \times qM$ HR image in lexicographic order, q is the magnification factor, W is a $NM^2 \times q^2 M^2$ matrix representing the geometric shift, blur, and down-sampling operator which operates on z to yield y, and n is the independent identically distributed (i.i.d.) Gaussian noise with a probability density function (pdf) given by

$$\Pr(n) = \frac{1}{2\pi^{\frac{p}{2}}\sigma_\eta^p} \exp\left(-\frac{1}{2\sigma_\eta^2} n^T n\right) \qquad (2.5)$$

A MAP estimate of the HR image z can be computed as:

$$z = \arg\max\{\log \Pr(z|y)\} = \arg\ \min\{-logPr(y|z) - logPr(z)\} \quad (2.6)$$

Commonly, the prior image model is chosen to be Gauss-Markov-random-field-based model, and the density has the form of:

$$\Pr(z) = \frac{1}{(2\pi)^{\frac{k}{2}} |C_z|^{1/2}} \exp\left(-\frac{1}{2} z^T C_z^{-1} z\right) \quad (2.7)$$

where C is the covariance matrix of z. Substituting (2.4), (2.5), (2.7) into (2.6), after some manipulation, we get:

$$\hat{z} = \arg\min\{\frac{1}{2\sigma_\eta^2}(y - Wz)^T(y - Wz) + \frac{1}{2} z^T C_z^{-1} z\} \quad (2.8)$$

Two-dimensional Gabor wavelets are defined as:

$$\Psi(k, r) = \frac{\|k\|^2}{\sigma^2} exp\left[-\frac{\|k\|^2 \|r\|^2}{2\sigma^2}\right]\left[\exp(ikr) - \exp\left(-\frac{\sigma^2}{2}\right)\right]$$

(2.9)

where r is the image pixel coordinate, k determines the orientation and scale of Gabor kernel. Their experiments showed that recognition rate is 95%, which demonstrates that Gabor feature based SR reconstruction and recognition could work fairly well on LR face image sequences.

2.5.3.4 multidimensional scaling (MDS)

In [38], a novel approach for improving the matching performance of LR images using multidimensional scaling (MDS) is proposed. Their goal is to find a transformation matrix that the distance between transformed features of LR images can be as close as possible to their corresponding HR images. Let I^h and I^l represent for HR and LR images, and W is the transformation matrix. The objective function is described as following:

$$J(W) = \lambda \sum_{i=1}^{N} \sum_{j=1}^{N} (\left| W^T \left(\phi(I_i^l) - \phi(I_j^l) \right) \right| - \left| \phi(I_i^h) - \phi(I_j^h) \right|)^2 + (1 - \lambda) \sum_{i=1}^{N} \sum_{j=1}^{N} \delta(w_i, w_j) |W^T(\phi(I_i^l) - \phi I_j^l))|^2 \qquad (2.10)$$

where $\phi(x)$ can be a linear or non-linear function of the input feature vectors, which controls the relative effect of the distance preserving and the class separability on the total optimization. A simple way of make use of class in-formation is that (Ii; Ij) is set to one when Ii and Ij are from the same class and otherwise it is set to zero. This specific form makes sure the distance between data from the same class to be small. The iterative majorization algorithm is used to minimize the objective function.

In testing phase, for input image *Iinput*, the transformed feature *Iinput* is obtained by

$$\hat{I}_{input} = W^T \phi(I_{input}) \qquad (2.11)$$

Euclidean distance is then computed for classification.

Their experimental evaluation shows that this method performs better than bi-cubic interpolation and a super-resolution method using sparse representation [39].

2.5.3.5. Face Super Resolution Reconstruction and Recognition Using Non-local Similarity Dictionary Learning Based Algorithm

Hao et al. [40] define and prove the multi-scale linear combination consistency. In order to improve the performance of SR, they propose a novel SR face reconstruction method based on non-local similarity and multi-scale linear combination consistency (NLS-MLC). They further proposed a new recognition approach for very low resolution face images based on resolution scale invariant feature (RSIF).

In [40], a novel face hallucination method based on non-local similarity and multi-scale linear combination (NLS-MLC) is presented. NLS-MLC contains two phases: the training phase and the reconstructing phase. During the training phase, HR and LR image patch dictionary pair is learnt from training face image samples. During the reconstructing phase, the output HR image is generated based on the same linear representation of the tested image with respect to the dictionary pair. Detailed steps of this algorithm are discussed in the following.

The training phase: a) Determine the degradation process, including the noise variance and fuzzy parameters, based on the observed LR input image and the HR image samples. b) Generate the corresponding LR image samples by degrading each HR face image through the same degradation process. c) Each HR or LR image is divided into a set of small corresponding image patches with overlap, the patch size of the HR image is $bs \times bs$ and the LR image $b \times b$, where s is the down-sampling factor. 2) The reconstructing phase: a) Divide the input LR image into $b \times b$ patches with overlap in the same way as processing training LR samples. b) gray correlation analysis (GCA) [41] is applied to measure the similarity among image patches for searching non-local similar patches. RSIF can avoid the process of SR face reconstruction and is robust to resolution variations. It consists of three steps: data pre-processing, coefficients calculation and recognition. 1) Data pre-processing: Firstly, manually align and crop face images to the same size. Secondly, generate the corresponding LR face image space from degradation of the HR images. Thirdly, divide these images into patches

And search their non-local similarity patches. 2) Coefficients calculation:
Assume that image patch Y (i, j) can be represented as the linear combination of its similar image patches:

$$Y(i,j) = \phi_{i,j}^{L} W^{L} \tag{2.12}$$

where $\phi_{i,j}^{L}$ is the set of non-local similar image patches in the LR dictionary.

For the PCA+1NN face recognition algorithm, PCA is used to extract the eigen faces (Eigenfaces is the name given to a set of eigenvectors when they are used in the computer vision problem of human face recognition. Specifically, the eigen faces are the principal components of a distribution of faces, or equivalently, the eigen vectors of the covariance matrix of the set of face images, where an image with N pixels is considered a point (or vector) in N-dimensional space.)

as the feature for the 1NN classifier. The gap between recognition accuracy of VLR images and HR images is around 20 %. Existing SR algorithms such as EF and DSR can slightly improve the recognition accuracy of VLR images whereas KF and PF even worsen the performance to some extent. However, the NLS-MLC method can improve the performance significantly. The approach uses the same classifier but changes the feature extractor from PCA to kernel PCA (KPCA) and repeat the experiments. The recognition accuracy of their method approximates that of the original HR images.

The proposed RSIF method in [40] can improve the performances for all of the three resolutions. For images of 7 × 6, the recognition rate of RSIF approximates that of the original HR images. For images of 14 × 12, and 28 × 24, the performances of RSIF are even better than that of the original HR images. Moreover, the recognition rates of RSIF on three different resolutions are nearly the same. This means that RSIF is robust to resolution variations and can be used to solve VLR face recognition problem.

2.5.3.6 coupled locality preserving (CLPM)

In [42], a SR method using coupled locality preserving mappings (CLPM) is proposed. This method requires HR and LR image pairs for training. The main idea is to obtain coupled mappings which can project both HR and LR image features to a unified feature space so that direct comparison of HR and LR in that feature space could be possible.

The objective is to make sure the projections of LR images and their corresponding HR images would be as close as possible in the new unified feature space. Let I^h and I^h be the HR and LR images, this can be formulated as:

$$J(f_L, f_H) = \sum_{i=1}^{N} \left\| P_L^T I_i^l - P_H^T I_i^h \right\|^2 \qquad (2.13)$$

where PL and PH are the transformation matrix from LR and HR image space to the unified feature space. They can obtain the mappings by minimizing this formula. The gallery and probe images then will be mapped to a unified feature space where we can use nearest neighbor classifier for recognition.

This method has good performance on face recognition. Besides, it is more suitable for real-time systems because the test process can be very fast once the training part is done offline.

Chapter 3: Proposed APSR algorithm

In this chapter, we first discuss the stages of face recognition, then we propose an algorithm to solve the LR images problem that occurs in the testing stage (face recognition at a distance), the proposed algorithm is called Average Pixel Super Resolution (APSR), we explain the algorithm in details, its principle, requirements, and how it solves the problem we faced.

3.1. Face Recognition Algorithms:

In general, face recognition goes through two main stages: training and testing stages that each of them has multiple steps to finally recognize a person. These steps, depending on the recognition algorithm will be used are as follow:

Training Phase:

First, high resolution images are taken from facial database and analyzed using the histogram algorithm discussed in the next section. The algorithm used here called Histogram- POC algorithm but in our work we used only Histogram part of it, the POC part is not used here. The output of this process is a value represents the image. Each image has a correspondent value that will be used to find the most match image by storing values of each image in a binary search tree. Figure 4.1 demonstrates the training phase stage:

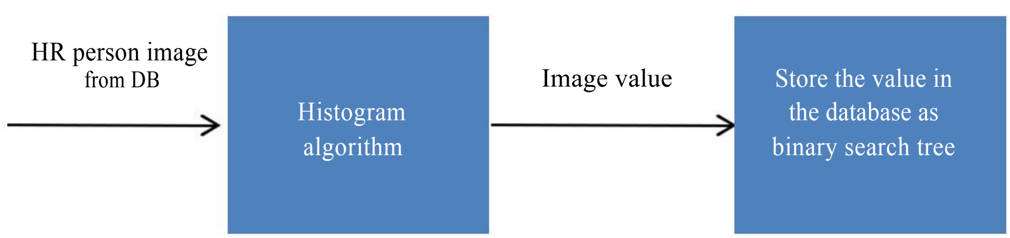


Figure 4.1: Block diagram for training phase stage

Testing Phase:

The low-resolution image is entered to an algorithm that constructs the corresponding high-resolution image in order to use it for comparison reasons because we can't compare low resolution image values with high resolution image values (either high resolution with high resolution or low resolution with low resolution). Therefore, as mentioned, we will enter the LR image to our proposed algorithm Average Pixel Super Resolution (APSR) that will be discussed in later section. The output of that process is a constructed high-resolution image from the low resolution image. In a following step, the image produced is entered to Histogram-POC algorithm used in the training stage to find its value. Finally, we compare the value resulted from the test image and the values in the binary search trees (values of training stage images) to determine the closest value representing the most-matched person. In a further step, the system displays the recognized person.

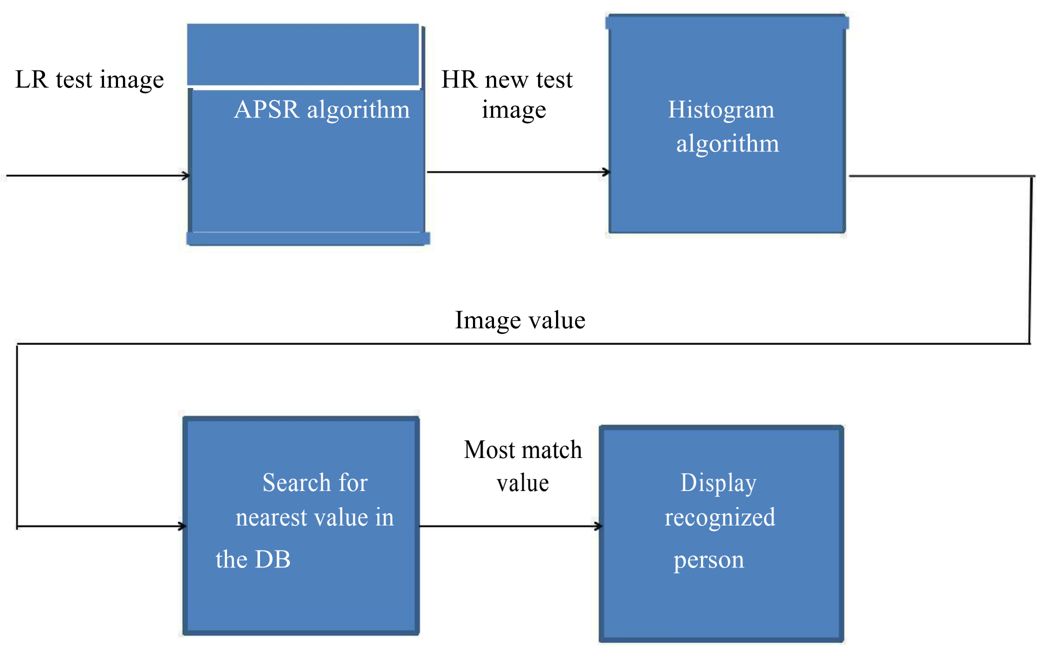


Figure 3.2: Block diagram for testing phase in face recognition

3.1.1 Histogram-phase only correlation (POC)

A histogram is a display of statistical information that uses rectangles to show the frequency of data items in successive numerical intervals of equal size. Histogram modeling techniques (*e.g.* histogram equalization) provide a sophisticated method, which automatically minimizes the contrast in areas too light or too dark of an image, consists of a nonlinear transformation that it considers the accumulative distribution of the original image, to generate a resulting image whose histogram is approximately uniform [43].

Unlike contrast stretching, histogram modeling operators may employ non-linear and non-monotonic transfer functions to map between pixel intensity values in the input and output images.

3.1.1.1 Histogram Processing

The plot of frequency of occurrence of various gray levels of an image is known as histogram. Since images have many types, so their histograms depend on these types [44]:

1- Binary image: this means that every part of the picture will be either white or black, so its histogram will be only two values. One of them is the frequency of black pixels, and the other is the frequency of the white ones as shown in Figure 3.3 [45]:

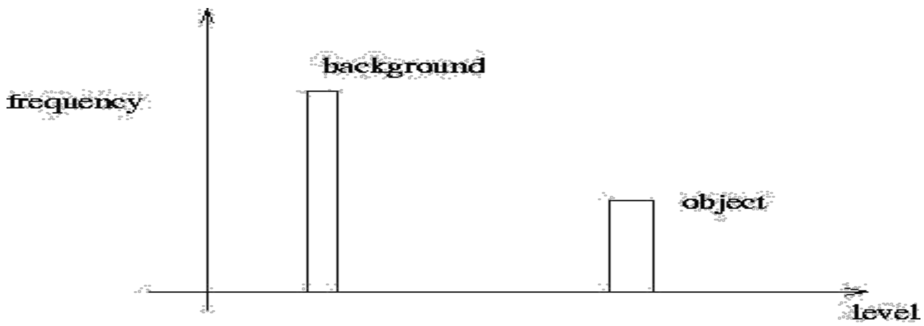


Figure 3.3: Binary image histogram.

2- Gray scale images: it is 256 levels so the histogram will be 256 pins, where each pin expresses one gray level. The peak of each pin is showing the frequency of pixels having that level in the image as shown in Figure 3.4 [44]:

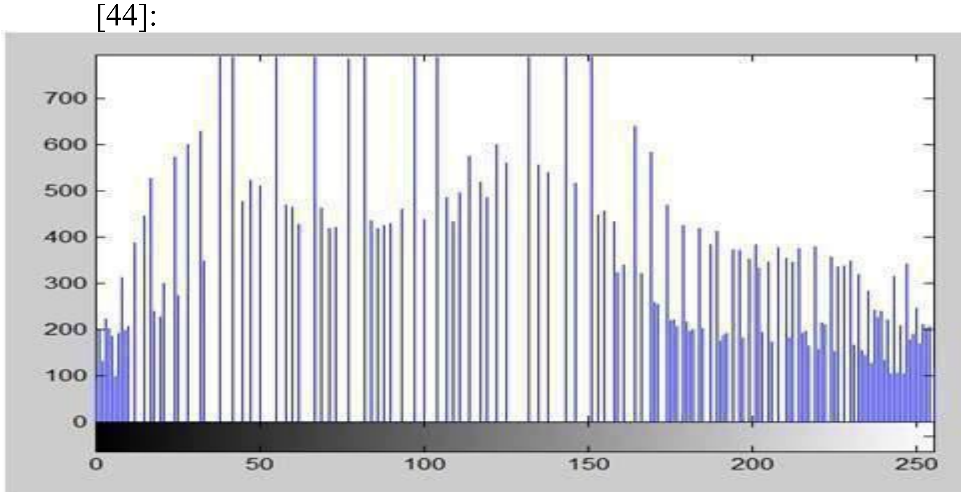


Figure 3.4: Gray scale image histogram.

Histogram of face images:

For obtaining face image histograms, in the first place, the 256-level histogram must be created, and then each 8 contiguous levels are represented as one value in order to simplify calculations and comparison as well as to accelerate the image processing without affecting the quality of the image. After this process, there will be 32 pins (peaks) only instead of 256 pins, whose peaks are the sum of the 8 levels frequencies [44].

This process is repeated for each image in the database (training process), and at the end, there will be values for each image and for the test image for comparing values of the test image with values of all images in the database to find the most similar image.

The above method is blind but rotation invariant in nature and is considered to be a global approach for face recognition. In worst case scenario, two altogether different images may have almost same histograms, so this ambiguity is further verified using Phase-Only Correlation discussed in next section [44].

3.1.1.2 Phase-Only Correlation (POC)

Phase-Only Correlation is an approach to estimate the relative offset between two similar images, which relays on frequency domain representation of the data and is considered as 2D Discrete Fourier Transform (2D DFTs) of the two images [44].

Let’s consider two images of size N1 X N2 as f (nl, n2) and g (n1, n2). Let F(k1, k2) and G(k1, k2) be their 2D discrete Fourier transforms, then their cross-phase spectrum or normalized cross spectrum RFG is defined as the conjugate of G(kI, k2) multiplied by F(k1, k2) divided by its absolute value as in Eq. 3.1:

$$R_{FG}(K_1, K_2) = \frac{F(K_1, K_2)\overline{G(K_1, K_2)}}{\left|F(K_1, K_2)\overline{G(K_1, K_2)}\right|} = e^{j\theta(K_1, K_2)} \qquad (3.2)$$

When 2D Inverse Fourier Transform (2DIFT) is applied on (3.2), the POC function is generated as follow [46]:

$$r_{fg}(n_1, n_2) = \frac{1}{N_1 N_2} \sum_{k_1, K_2} R_{FG}(K_1, K_2) W_{N_1}^{-K_1 n_1} W_{N_2}^{-K_2 n_2} \quad (3.2)$$

From Equation (3.2), there are many benefits from using the POC in face recognition work. One important benefit from using POC is when the two images are similar the POC gives distinct peak, but when the images are dissimilar there is no distinct peak, meaning that it drops down as shown in figure 3.5 [47].

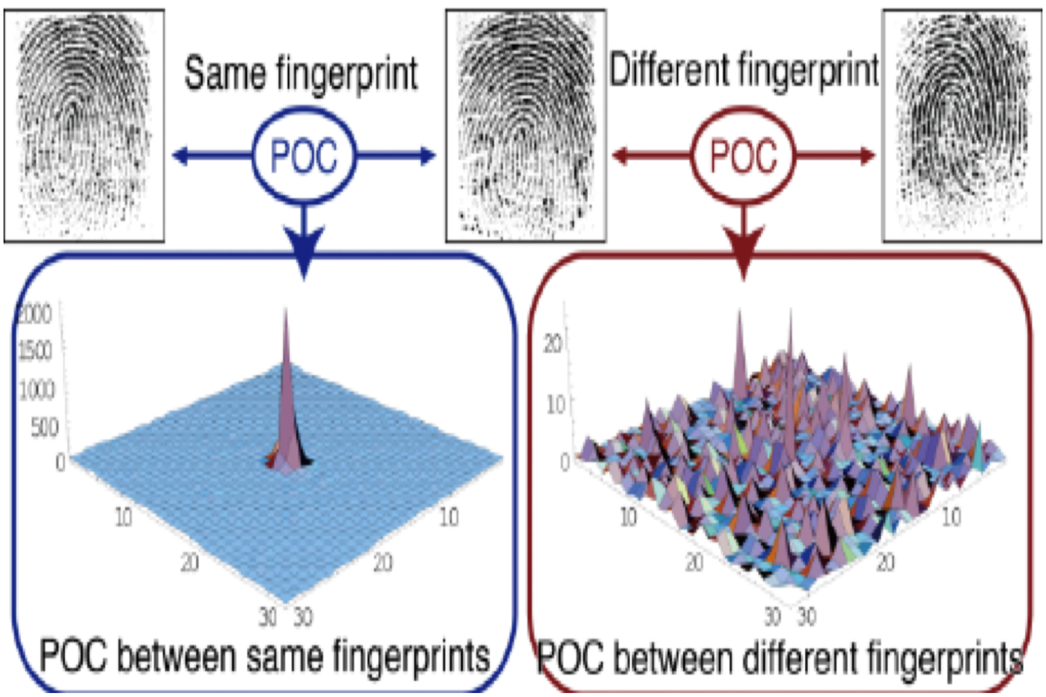


Figure 3.5: Phase Only Correlation (POC)

3.1.2 Face recognition Technique used in this thesis

For getting better performance of face recognition, merger of histogram and Phase-Only Correlation (POC) techniques is used in implementation of the suggested system.

For training, images are converted to gray with 256 levels. To achieve this, firstly, compute frequency of each level in the image, and then store them in vectors for further processing. Secondly, mean of contiguous eight frequencies from the stored vectors is calculated and are stored in another vectors for later use in testing phase. Such a vector is used for comparing between the test image and the database images. Finally, the minimum difference found identifies the matched person.

The algorithms used for training and testing are shown in Figure 3.6 and 3.8 respectively.

```
Procedure: Training
Input: Five (5) images from every subject (40) of
ORL
Begin

1. Calculate frequency of every bin and store
in matrix.
2. Calculate mean of consecutive eight
frequencies and store in matrix for
later comparison.
end
```

Figure 3.6: Training stage of face recognition [44]

Procedure: Testing

Input: images from every subject from database that are not used in training.

Output:

* Absolute processed histogram differences.
* matched subject.

Begin

1. Calculate frequency of every bin of test image.

2. Calculate mean of consecutive eight frequencies of test image.

3. Compare the means of test image with all trained matrix mean values of training algorithm

4. Identify the image with minimum absolute difference.

5. Compare POC values with cutoff value for verification.

6 .display the recognized person.

End

Figure 3.8: Testing stage of face recognition algorithm [44]

3.2 Super resolution methods

Section 2.5.3 provided description of some of the methods used to obtain SR from LR images. In this section we discuss the proposed APSR method. Super resolution method for low resolution images is proposed in this thesis to make the recognition of far distance low resolution images as efficient as that with high resolution images.

3.2.1 Average pixel super resolution method (APSR) method

The APSR approach is used in the testing stage, it stands with the detection of face from the whole image and then the construction of high resolution face image by fully utilizing each pixel information provided in the low resolution image. Finally, Histogram-POC algorithm [44] is used to compare the high resolution image produced from the method mentioned above with images in the database to find the most matching face. APSR goes through two steps to achieve this:

a) **Face detection:**

using Matlab algorithm to find and locate the face in order to crop it from the image. Use the vision.CascadeObjectDetector to detect the location of a face in a video frame. The cascade object detector uses the Viola-Jones detection algorithm and a trained classification model for detection. By default, the detector is configured to detect faces, but it can be configured for other object types [49].

Figure 3.9: Detecting and cropping a person face.

b) Construct HR image from LR image:

The construction process is divided into two parts, at the first part the LR image is analyzed and operated pixel by pixel. Each pixel in the input LR image is expanded to be 4 pixels in the new image as following: lets say we have an image consisting of only 4 pixels (p(0,0), p(0,1), p(1,0), p(1,1)) as Figure 3.10 (a) shows, as LR image, after applying APSR algorithm we will obtain an image consisting of 16 pixels, because each of the four pixels in the original image will be expanded to be 4 pixels. The values of the new pixels will be as following:

Lets take pixel p(0,0) as an example: p(0,0) has p(0,1) as right neighbor and p(1,0) as below neighbor, so when expanding p(0,0) pixel we will have four pixels with values calculated as follows :

1. p(0,0) value stay as it, and stay in its place.
2. Adding new pixel to the right to p(0,0) with value equals (Avg(p(0,0),p(0,1)) lets call it X_{pixel} .
3. Adding new pixel below p(0,0) with value equals (Avg(p(0,0),p(1,0)) lets call it Y_{pixel} .
4. Adding new pixel on the diagonal with p(0,0) with value equals (Avg(X_{pixel}, Y_{pixel})) lets call it F_{pixel}.

   The process mentioned is explained in Figure 3.10:

LR

P(0,0)	P(0,1)	
P(1,0)	P(1,1)	

HR

P(0,0)	Avg(P(0,0) ,P(0,1)-----> Y pixel	P(0,1)
Avg(P(0,0) ,P(1,0)-----> X pixel	F= AVG (X pixel , Y pixel)	
P(1,0)		P(1,1)

a) LR input image b) HR constructed image

Figure 3.10: a) LR input image b) HR constructed image

We repeat those steps with all pixels in the LR image to finally have anew image witch is four times the old LR image and the first part is finished.

since any image is treated as two dimensional matrix with x rows and y columns, so in our work we will find new pixels in each row and each column (X_{pixels} and Y_{pixels}) , also we should take in consideration that the value of each pixel is a compound of three values (red , green , blue) depending on RGB color system, also that the global RGB system express the three colors in the following order: red, green, blue. So to find the value of the new pixel we must find the value of its three compounds values first. The values for each pixel are calculated using matlab as follows (we should note that matlab dealing with RGB system as 3 layers such as: layer 1 is RED, layer 2 is GREEN, layer 3 is BLUE):

$$Y_{red}(new) = avg(p(i,j,1) + p(i, j+1 ,1)) \qquad (3.3)$$

$$Y_{green}(new) = avg(p(i,j,2) + p(i, j+1 ,2)) \qquad (3.4)$$

$$Y_{blue}(new) = avg(p(i,j,3) + p(i, j+1 ,3)) \qquad (3.5)$$

$$x_{red}(new) = avg(p(i,j,1) + p(i+1, j ,1)) \qquad (3.6)$$

$$x_{green}(new) = avg(p(i,j,2) + p(i+1, j ,2)) \qquad (3.7)$$

$$x_{blue}(new) = avg(p(i,j,3) + p(i+1,j,3)) \quad (3.8)$$

$$F_{red}(new) = Avg(X_{red}(new), Y_{red}(new)) \quad (3.9)$$

$$F_{green}(new) = Avg(X_{green}(new), Y_{green}(new)) \quad (3.10)$$

$$F_{blue}new) = Avg(X_{blue}(new), Y_{blue}(new)) \quad (3.11)$$

As we have said previously that each pixel in the input LR image is expanded to be a patch of pixels in the new HR image , so we express each pixel in the LR image (P_{old}) as 4 pixels in the HR image (P_{new}) each one of them have a value described as follow:

$$\forall_{p_{old}(i,j)} \longrightarrow \begin{cases} P_{new}(i,j) = P_{old}(i,j) \\ P_{new}(i,j+1) = Y_{avg} \\ P_{new}(i+1,j) = X_{avg} \\ P_{new}(i+1,j+1) = Avg(X_{avg} + Y_{avg}) \end{cases}$$

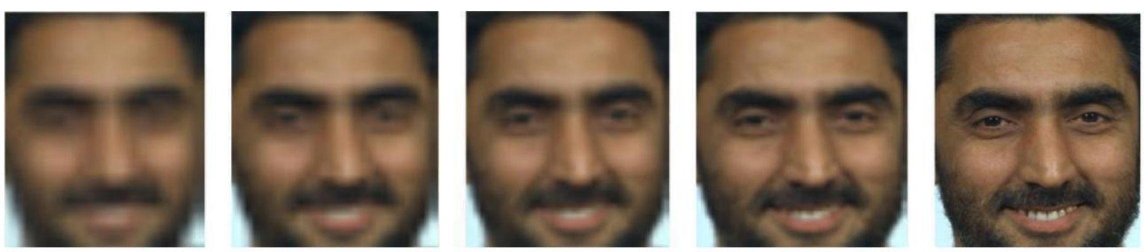
part two: Image Enhancement

Now at the second part of the algorithm the goal is to be sure that the reconstructed image is suitable to be compared with the HR images in the database, this is done by using a threshold value we calculate it, if the new image is above that threshold then we can say that it is ready to be tested, but if it is not above the threshold then we resort to repeat part one more and more until reach the required threshold.

The threshold value is calculated by experiments, we found that if the constructed image resolution is approximately 80% of the HR image resolution or above the comparison is applicable and the performance of the recognition is effective

If D<threshold
Then → HR test image is constructed and ready to use
Else
Repeat: stage one

As we can see from figure 3.11, we used figure 3.11(e) is the original image with resolution 768*512 we resized the image using matlab to be Fig. (3.11 a) with resolution 95*70, firstly we entered that Figure to our algorithm, Fig. (3.11 b) was generated (with resolution 190*135) and tested if we can compare it with the database images, we found that the distance between it and the original image was nearly 6% of it, but that distance was not enough, so we should take that image and enter it again to APSR algorithm and we get Fig. (3.11 c) with resolution400*250, we repeat the same previous process, we found that the generated image is approximately 25% from the original image, we still less than the threshold, so we again use APSR method, and obtain an image with result 750*500, witch is 95% from the original image, it is above the threshold (80%), and very close to the database images and we can use it in testing phase.



a) b) c) d) e)

Figure 3.11: a) LR input image(b) after stage 1 c) after repeating stage 1 d) final HR image after applying our algorithm e)original HR image(7

As previously mentioned we will enter the LR image to our algorithm APSR (Average Pixel Super Resolution) that analyzes the image pixel by pixel , by entering the pixel's values to equations(3.3 – 3.11) in order to calculate values of new pixels that will be used to construct the new HR image , then we calculate the distance (D) between the new HR image and HR images in the database , if that distance is less than a specified threshold then the new HR image is close enough to images in the database and can be compared to them , by entering it to the (Histogram) algorithm , obtaining value that compared to training images values , and finally find the most match person, as shown

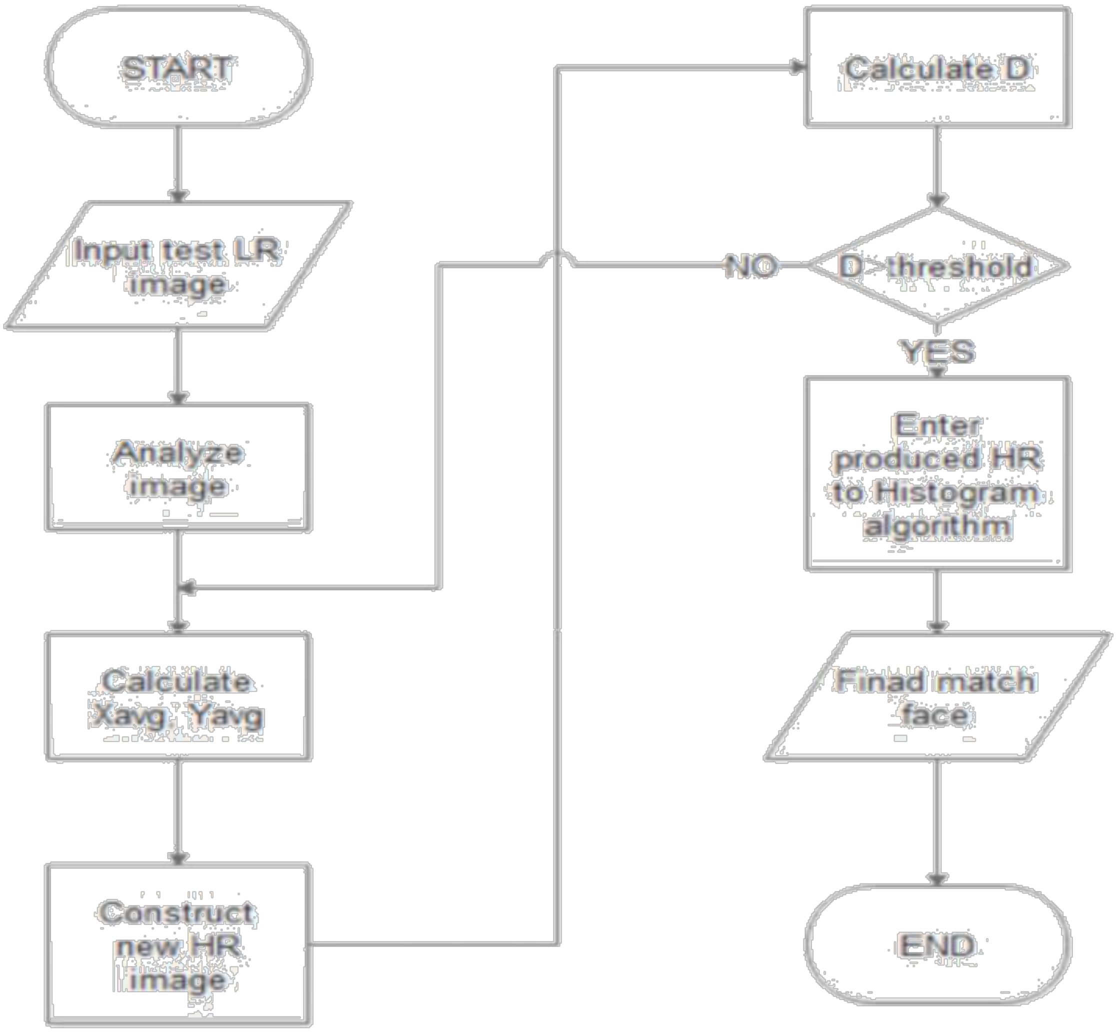


Figure 3.11: Flow chart of proposed the algorithm

Figure 3.12 explains the implementation of the algorithm using matlab: as we said previously any image is treated as group of rows and columns, so when we want to test an image and recognize persons from it we first calculate the distance between its resolution and the resolution of HR images in the database, if the value calculated is less than 80% of the resolution of database images then we consider the input image as a LR image that need enhancement process to be suitable for testing. The construction process is started by taking all pixels in the LR image one after another until reaching the last one. The mentioned process goes as follows: each taken pixel is expanded to be 4 pixels by finding Yavg which is a new pixel will be added to the right of the original expanded pixel, Xavg to be added below the expanded pixel, and finally finding the value of the fourth pixel which is the average of Xavg and Yavg and it is added on the diagonal with the expanded one. After calculations for the pixel is finished the pixel and new pixels are added to the new image which we call (img2), when we reach the last row and the last column then the new image is ready. Now we calculate the distance again if it is greater than the threshold, the image goes through testing phase, if not repeat the whole process again.

```
img = rows*columns
IF D<threshold THEN
   For i=1 to rows
       For j=1 to columns
           IF it is not last column THEN
              compute Y(new)= Yavg as average of (img(i,j) and img(i,j+1))
           END
           IF it is not last row THEN
              compute X(new)=Xavg as average of (img(i,j) and img(i+1,j))
              compute fourthAverage as average of (Xavg and Yavg)
           END

           for i'=i*2 to i*2+1
               for j'=j*2 to j*2+1
                   substitute img2(i',j')= img(i,j)
               END
               IF it is not last column THEN
                  img2(i',j*2+1)=Yavg
               END
           END
           IF it is not last row THEN
              img2(i*2+1,j*2)=Xavg
              img2(i*2+1,j*2+1)=fourthAverage
           END
       END
   END

 ELSE
    Test(img2)
END
```

Figure 3.12: Pseudo code for proposed algorithm.

3.3 Searching in the database

As we discussed in section (2.2), face recognition steps are:

1. Step one: enter images to the database using the Histogram algorithm.
2. Step two: enter the LR test image through the APSR method in order to find the new HR image then, enter the obtained HR test image to Histogram process.
3. Step three: compare test image value with the value of images in the database, We use binary search instead of linear search that is used in many researches because of the fact that it makes the whole process very fast and reduces the processing time to less than half the time. In other words, it reduces the time complexity from ***O(N)*** to ***O(log(N))***.

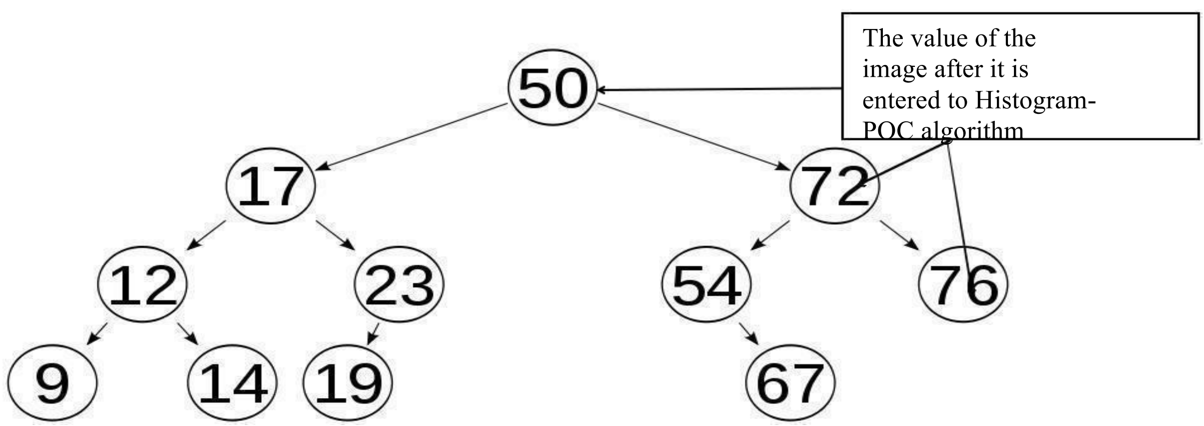


Figure 3.13: binary search tree for training images values.

At the end, we represent information acquired from all HR images in the database as a binary search tree as presented in Figure 3.13. This tree helps us to find the most matched value to the value resulted from entering the constructed test HR image to the Histogram- POC algorithm.

4. Step four: recognize the person and the name of the person to whom the HR image belongs in displayed.

Chapter 4: algorithm Verification Analysis

4.1 Color FERET database

Color FERET database is standard database used for face recognition systems and researches. The FERET image corpus was assembled to support government monitored testing and evaluation of face recognition algorithms using standardized tests and procedures. It is a large data set of face images [50]. For more details see Appendix B.

4.2 Super resolution results

Depending on the experiments conducted, the recognition performance of low resolution images is being affected. Effort is needed to improve these results. An intuitive way is to apply super-resolution on the low-resolution images to enhance the image quality. In this section, we will show results of some of super resolution algorithms mentioned in section (2.5.3), then we will apply proposed (APSR) algorithm to show its results and evaluate its performance in contrast with the others .

4.2.1 Results of the various SR algorithms

the results of experiments are summarized on the following table after that details of some algorithms is mentioned:

No	Authors	Feature Extraction and Classification Tech	Data	Results
1	Sivaram Prased Mudunuri , Soma Biswas 2015	Multidimensional scaling to learn common transformation matrix for the entire face ,using SIFT descriptors.	Tested using three data sets (Multi-PIE dataset , Surveillance Cameras Face Database ,Multiple Biometric Grand Challenge database)	80% - 93%
2	Di Zhang , Jiazhong He 2010	Constructs a high resolution face image by fully utilizing the sub-pixel information from the LR sequences and then performs Gabor feature based recognition.	20 faces from AR database	95%
3	Ningbo Hao, Haibin Liao, Yiming Qiu, Jie Yang 2016	Reconstruction method based on non-local similarity and multi-scale linear	Tested on two databases (FRGC V2.0 , and CAS-PEAL) databases	96%
4	P. H. Hennings-Yeomans, S. Baker, and B. V. K. V. Kumar 2008	Simultaneous super- resolution and recognition . This approach simultaneously provides measures of fit of the super-resolution result, from both reconstruction and recognition perspectives	Tested on three databases (Multi-PIE , FERET , and FRGC) databases	80%
5	S. Biswas, K. W. Bowyer, and P. J. Flynn 2010	Multidimensional scaling for matching low-resolution facial images. The goal is to find a transformation matrix that the distance between transformed features of LR images .	Tested using PIE dataset And FRGC database	75% and 90%

Table 5: summery of far distance face recognition algorithms and their experiments.

Now details of experiments of two algorithms mentioned in table are displayed:

1. Coupled cross-regression for low-resolution face recognition

The experiments are based on the standard gallery (1196 images) and the probe set "fa fb" (1195 images). For CMU PIE, 1428 frontal view face images with neutral expression and illumination variations in 68 subjects (21 images per subject) were selected in the experiment. For each subject, three images are randomly selected for training and the remaining 18 images for testing. Here only one image with no flash illumination is taken as gallery, while the probe set contains the images with different illuminations (17 images per subject). One sample in the FERET and CMU PIE with the HR size 72 × 72 and 64 × 64 respectively and the corresponding LR size 12 × 12 and 8 × 8. [51].

For 12 × 12, their CCR method achieves the rank-1 recognition rate of 90.5%, which outperforms state-of-the-art structure-based methods CLPMs (89.7%) and SDA (90.2%). However, the performance of CCR1 (88.5%) is worse than CCR even CLPMs. On the other hand, the recognition rates of LR-LGE methods, i.e., NN-LDA, NN-LPP and NN-SR (LDA) are only 71.7%, 65.2% and 74.6% respectively and much lower than CCR.

For 8×8, although the performances of all methods more or less decline, their CCR method still achieves 75.9%, and outperforms CLPMs (68.7%) and SDA (73.5%). And the performance gap between them is larger than that in 12×12. It implies that CCR has a great potential in solving very LR problem. Moreover, the performance of CCR1 (70.9%) is slightly better than CLPMs but poorer than CCR and SDA. Compared with CCR, the performances [51].

2. Face super-resolution reconstruction and recognition from low-resolution image sequences

A total number of 20 faces were selected from AR database. To make a comprehensible comparison, 6 different face recognition techniques were tested, including:

1)Eigenface recognition with a single LR face image.

2)Gunturk's Eigenface-based method.

3)Construct a HR face first and then perform Eigenface recognition.

4) Eigenface recognition with original HR face.

5) Gabor feature.

6)Gabor feature based recognition using the original HR face.

	Eigen face				Gabor feature	
	1	2	3	4	5	6
recognition rate	40%	70%	75%	80%	95%	95%

Table 6: Results of Face super-resolution reconstruction and recognition from low-resolution image sequences using several methods.

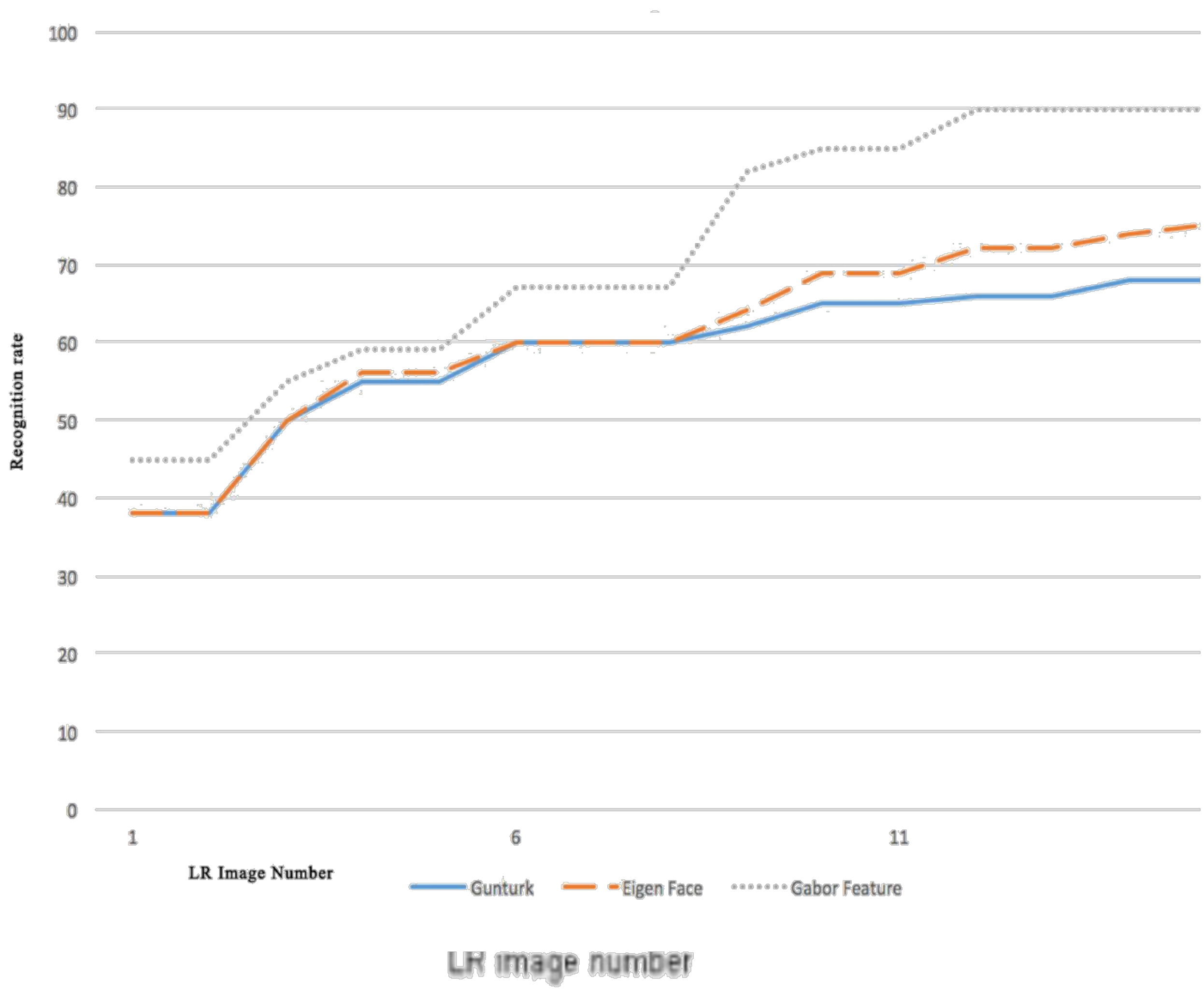


Figure 4.1: results of Face super-resolution reconstruction and recognition from low-resolution image sequences using several methods.

4.2.2 Experimental Results of APSR

Configuration

The 700 Images is total of 70 subjects (persons), with 10 images per person were taken from COLOR FERET database have a resolution of (768*512) were used in this experiment (see figure 4.3). Because the background and non-face parts of the images would affect the result of super-resolution, the images used were cropped to obtain the face region only. Then the MATLAB function *imresize* with new size percentage parameter is used to re-scale these cropped images to 384*256, 192*128, and 96*64 pixels to use them as HR for training and LR for testing. The images were divided into training, and testing sets. Training set contained 560 images of 70 persons. Two images per person from the rest images were used as test images (140 images).

Figure 4.2: some of FERET database images

a) Face cropping

The first step in our work was to crop images to extract only faces from the original images. To achieve this, we used MATLAB face detection function (vision.cascadeObjectDetector, in addition to the step function), which returns coordinates of face corners. Then we draw box around the face and crop along the drawn rectangle.

Figure 4.3: Faces after cropping

b) Face recognition

First, the reconstruction of high resolution (HR) images using APSR (equation (3.3-3.11) was performed on test images set. The 560 images were used for this training stage that were analyzed using (Histogram algorithm [37]). The acquired information was stored in the database for each person. The 140 testing images were reconstructed and then entered to the same algorithm to extract information from them.

Images with resolution 768*512 were used as high resolution images, while low resolution images were used of the resolutions of 384*256, 192*128, and 96*64 pixels. Of course, as the resolution decreases the information acquired out from these images is also low too. In the experiment, we carry out the tests individually on each low-resolution image, starting with images with 96*64 pixel with different ranks (number of database images). The results of the test are shown in figures (4.5 – 4.7) and tables (6-8).

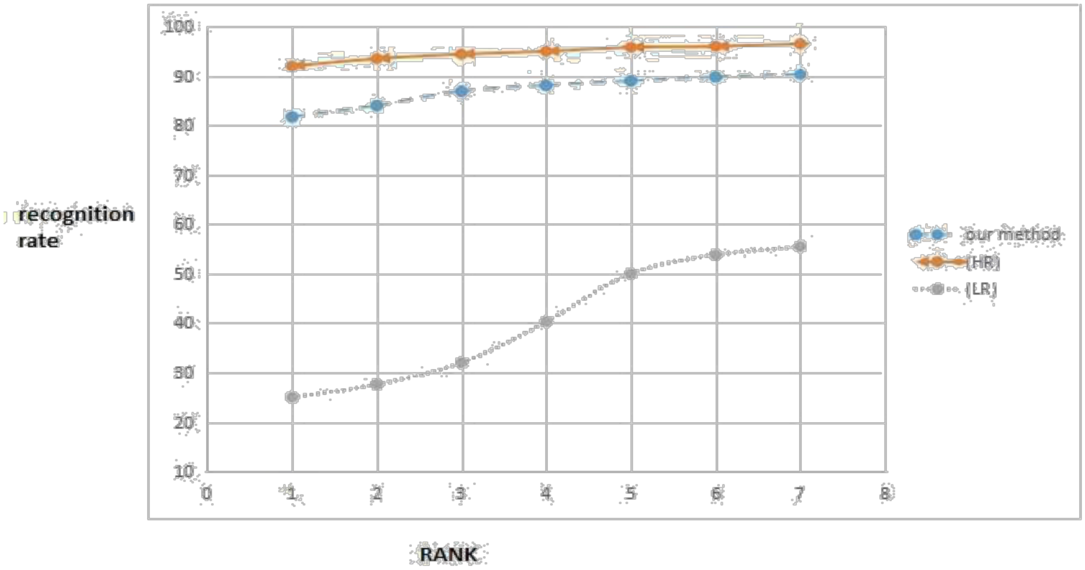


Figure 4.4: 96*64 pixel resolution results

Rank	Proposed APSR	HR	LR
1	81.7	92	25
2	84	93.5	27.6
3	86.9	94.4	32
4	88.1	95	40.3
5	89	95.8	50
6	89.8	96	53.8
7	90.3	96.5	55.5

Table 7: Results of applying (APSR) algorithm on 96*64 pixel images compared to LR and HR

In a further step, we continued with images with 192*128 pixels as low resolution images and then 768*512 as high resolution images. Also in this test, they are tested with different ranks (number of database images). The results of this stage are shown in Figure 4.6 and Table 7.

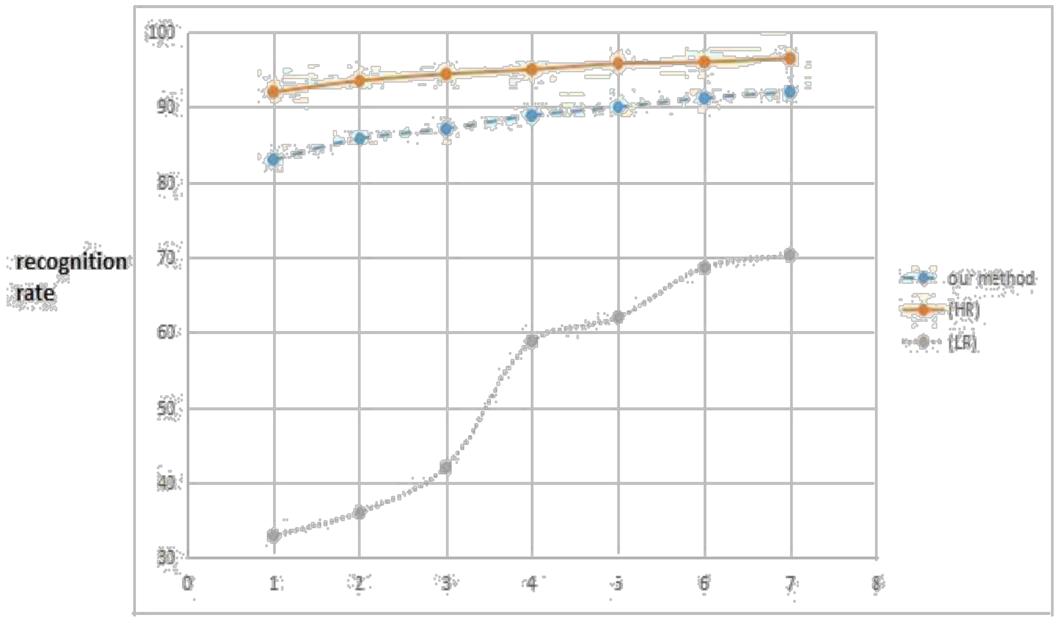


Figure 4.5: Results of testing imagers with the resolution 192*128

rank	Proposed APSR	(HR)	(LR)
1	83	92	32.9
2	85.8	93.5	36
3	87.1	94.4	42
4	88.9	95	58.8
5	90	95.8	62
6	91.2	96	68.6
7	92	96.5	70.3

Table 8: Results of applying (APSR) algorithm on 192*128 pixel images.

Finally, we tested the images with images of the resolution 384*256 representing LR images; the results are shown in Figure 4.7 and Table 8:

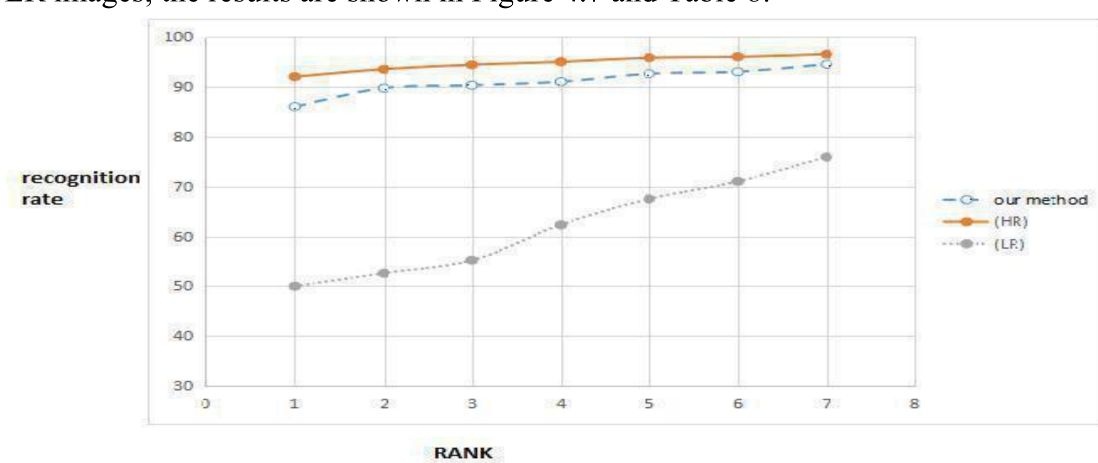


Figure 4.6: Results of testing imagers with the resolution 384*256

rank	Proposed APSR	(HR)	(LR)
1	86	92	50
2	89.7	93.5	52.6
3	90.3	94.4	55.2
4	91	95	62.3
5	92.6	95.8	67.5
6	93	96	71
7	94.5	96.5	75.9

Table 9: Results of applying (APSR) algorithm on 384*256 pixel images.

4.3 Comparison Between APSR and Other Algorithms

We evaluate the performance of the proposed (APSR) algorithm in comparison to the performance of other algorithms used for far distance face recognition, to make comprehensible comparison, 5 different far distance face recognition algorithms were tested; a) discriminative super-resolution (DSR) .b) nonlinear mapping on coherent features (NMCF) .c) Gabor feature based SR reconstruction and recognition d) Coupled cross-regression for low-resolution face recognition (CCR) .e) Proposed Average Pixel Super Resolution (APSR) .

From the recognition results shown in Figure 4.8: its clearly demonstrated that proposed algorithm gave performance which is better than most of them by approximately 5%-10%.

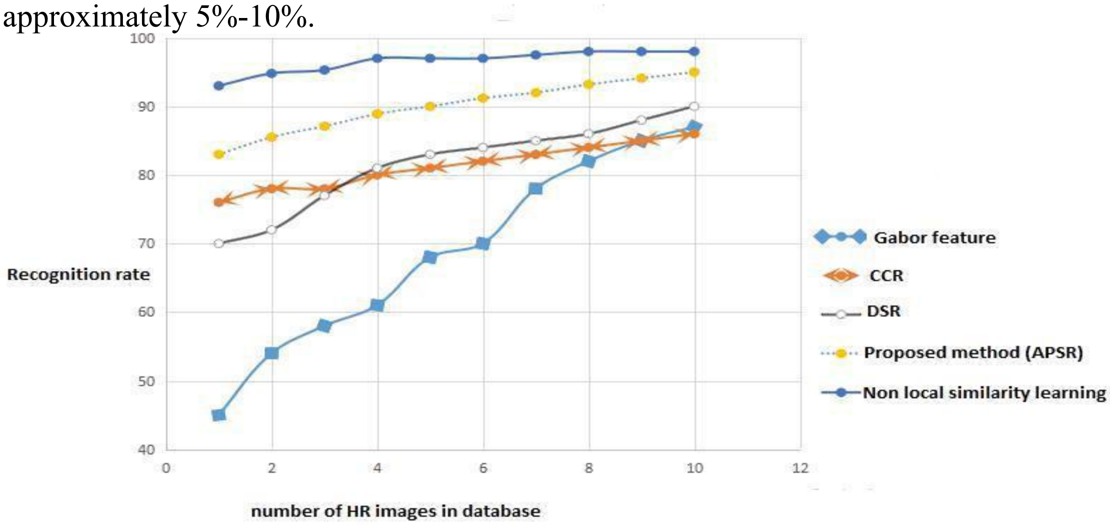


Figure 4.8: comparison between algorithms performance .

Also because binary search used here in searching the database to find the most matched person, the time needed to find the recognized person is reduced nearly half the time needed without using this approach (when using histogram as in [44] without binary search method the time needed is nearly 22 seconds for 400 images but here in our experiments with binary search and nearly 600 images it take ony 2-3 seconds.

4.4 Discussion:

From experiments described in section (4.2), as the resolution becomes lower, the recognition rate decreases but we can conclude that our proposed algorithm (APSR) can improve the recognition accuracy. APSR can be applied on several face recognition algorithms, we test histogram -POC algorithm [44], also from experiments we can notice that if we increase the number of training images in the database, the recognition rate will be better.

APSR improves the performance of recognition in many cases (at multiple distances). We tested three of them that represent three distances, first (384*256) nearly represents 3 meters, (192*128) almost 5 meters , finally last resolution (96*64) approximately 7 meters . The recognition rate is reduced as the distance increased, but it still nearly close to each other.

By applying binary search at searching stage to find the most matched person from the database, the time required to find that person from the database is decreased. In histogram -POC algorithm depending on results of [44] 22 seconds needed to recognize people. but by using binary search it takes only 2-3 seconds that represents (log)n)).

Pose variation might be a big problem as well, and the parts of the image (background and other parts except the face region) might make a problem in recognition process. One possible approach for future work is to apply better performance with pose, illumination in images, and applying on other databases with a different distance.

Chapter 5: Conclusion

In this report, the performance of face recognition using images with different resolutions is tested using Histogram- POC algorithm, first without using our proposed algorithm (APSR), then with it.

For experiments on FERET database in which the low resolution images (LR) are generated by using matlab (imresize) function, the recognition rate is steady when using high resolution (HR) images, and for images with resolution higher than a certain number (384*256).

When the resolution decreases the recognition rate obviously affected and goes down, because with lower resolution some of the information is lost also, it is observed that when using frontal faces from FERET database the recognition performance is better than when using images that have faces with pose.

Super resolution method (APSR) is used for improving the low resolution face recognition performance. The proposed method needs a training set containing HR images and testing set containing LR images, that are reconstructed by the algorithm.
APSR analyzes the image pixel by pixel, takes multi- average to find values of new image pixels, it provides an approach to construct a HR images and make sure that it is close to the original HR images in the training data set. The algorithm is applied on the input images to get their HR correspondents.

The (Histogram -POC) algorithm [44] is applied on the output HR images , find their values , and comparing it with values of database HR images to find the most match (recognized) person.

Experiments showed that face recognition performance improved as the resolution becomes greater and as the number of images in the training data set gets larger. On the other hand, as the resolution get lower, the recognition gets lower too, with a variation of nearly 5% between different resolutions. Add to that when using one image in the database, the recognition rate decreases by 10% compared to that when using seven images.

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Appendix A: Color FERET database

Color FERET database is standard database used for face recognition systems and researches. The FERET image corpus was assembled to support government monitored testing and evaluation of face recognition algorithms using standardized tests and procedures. It is a large data set of face images [50].

The database of facial images was collected between December 1993 and August 1996. In 2003, DARPA released a high-resolution, 24-bit color version of these images. The data set tested includes 2,413 still facial images, representing 856 individuals.

This database is largely a color version of the original Facial Recognition Technology (FERET) Database, which was released in 2001 and consisted of 14051 gray-scale images.

The database was created to develop, test and evaluate face recognition algorithms. To advance the state-of-the-art in face recognition, the Color FERET Database is made available to researchers in face recognition on a case-by-case basis only.

The images in the Color FERET Database are 768 by 512 pixels, and the files are in PPM-format: There are 13 different poses, from which the orientation "right" means facing the photographer's right [52].

fa	regular frontal image
fb	alternative frontal image, taken shortly after the corresponding fa image
pl	profile left
hl	half left - head turned about 67.5 degrees left
ql	quarter left - head turned about 22.5 degrees left
pr	profile right
hr	half right - head turned about 67.5 degrees right
qr	quarter right - head turned about 22.5 degrees right
ra	random image - head turned about 45 degree left
rb	random image - head turned about 15 degree left
rc	random image - head turned about 15 degree right
rd	random image - head turned about 45 degree right
re	random image - head turned about 75 degree right

Table 4: 13 different poses of FERET database.

Note that the rb, rc, and re angles are 5 degrees different from the estimated values that were used in the Gray FERET Database so that the angle increments would be more regular. A regular frontal image was captured for every subject at every capture session. In almost every case, a second frontal was also captured, and half- and profile- left and right images were usually captured as well.

Summary of Differences (gray and color) [52]

This database contains color versions of largely the same images that appeared in the Gray FERET Database. There are four other significant differences between this database and the Gray FERET Database:

The images' dimensions have been doubled to 512 x 768 pixels.

2- processing. Compression or processing artifacts are very visible in

many Gray FERET images when comparing them to their Color FERET

counterparts. The images have not undergone loss compression or any other

Numerous mistakes present in the Gray FERET Database have been fixed.

After examining the images on the Photo CD's, 96 images that were never labeled and released have been added to this database. The other 11242 originally appeared in the Gray FERET Database. (Actually, a small number of those are new images as well, where an image was erroneously in Gray FERET under multiple names, and the error was fixed by manually locating the image for the misnamed file name on the Photo CD's.)

Appendix B: Code Segments

Detect and crop face:

```
% Create a cascade detector object.
faceDetector = vision.CascadeObjectDetector();
% Create the webcam object.
%cam = webcam();

% Capture one frame to get its size.
%videoFrame = snapshot(cam);
%frameSize = size(videoFrame);

% Create the video player object.
%videoPlayer = vision.VideoPlayer('Position', [100 100
[frameSize(2), frameSize(1)]+30]);
runLoop = true;
numPts = 0;
frameCount = 0;
%for i = 1 : 7
   videoFrame =
imread('thesisPhotos1\OK\S12\9.ppm');%snapshot(cam);
  % videoFrame  =  imrotate(videoFrame,-90);
   %videoFrame = imresize(videoFrame,0.5);
  % videoFrame=imresize(videoFrame,0.5);
   bbox  =  step(faceDetector,  videoFrame);
   videoOut =
insertObjectAnnotation(videoFrame,'rectangle',bbox,'Eyes');
   imshow(videoOut);
   %step(videoPlayer, videoOut);
   for j = 1: size(bbox,1)
      w = bbox(j,:);

      img = imcrop(videoFrame,w)
     img = rgb2gray(img);
    img = rasha(img);
    imtool(img);
     img = faceRecog(img);
      display(img);
```

```
 recognationWithFaces(img);
     % imtool(img);
   % end
end
```

Construct HR image from LR image

```
for i = 1 : size(img,1)
        for j = 1 : size(img,2)
            if j < size(img,2)-1
               yavgr = (double(img(i,j,1))+double(img(i,j+1,1))) / 2.0;
               %yavgg = (double(img(i,j,2))+double(img(i,j+1,2))) / 2.0;
               %yavgb = (double(img(i,j,3))+double(img(i,j+1,3))) / 2.0;

            end
            if i < size(img,1)-1
               xavgr = (double(img(i,j,1))+double(img(i+1,j,1))) / 2.0;
               %xavgg = (double(img(i,j,2))+double(img(i+1,j,2))) / 2.0;
               %xavgb = (double(img(i,j,3))+double(img(i+1,j,3))) / 2.0;
            end
            for a = i*3 : i*3+2
                for z = j*3 : j*3+2
                    img2(a,z,1) = img(i,j,1);
                   %img2(a,z,2) = img(i,j,2);
                   % img2(a,z,3) = img(i,j,3);
                end
            if j < size(img,2)-1
               img2(a,j*3+2,1) = yavgr;
               %img2(a,j*3+2,2) = yavgg;
               %img2(a,j*3+2,3) = yavgb;
            end
            end
```

```
if i < size(img,1)-1 img2(i*3+2,j*3,1)
            = xavgr; %img2(i*3+2,j*3,2)
            = xavgg; %img2(i*3+2,j*3,3)
            = xavgb; img2(i*3+2,j*3+1,1)
            = xavgr;
            %img2(i*3+2,j*3+1,2)  =  xavgg;
            %img2(i*3+2,j*3+1,3)  =  xavgb;
            img2(i*3+2,j*3+2,1) = xavgr;
           % img2(i*3+2,j*3+2,2) = xavgg;
           % img2(i*3+2,j*3+2,3) = xavgb;

         end
     end
  end
```