# Color-Based Face Recognition with Different Color Spaces and Image Quality Assessment

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Submitted to the
Institute of Graduate Studies and Research
in partial fulfillment of the requirements for the degree of

Master of Science
in
Computer Engineering

Eastern Mediterranean University
June 2020
Gazimağusa, North Cyprus

Approval of the Institute of Graduate Studies and Research

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# ABSTRACT

Image quality is a critical issue for the recognition of faces because it reduces the risk of forging face recognition systems. The most relevant face spoofing attacks reported in previous studies follow one of the three trends: mobile attacks, high-def attacks, or print attacks. Spoofing attacks have prompted the biometric research community to learn more about the threat posed by these kinds of attacks on many biometric traits such as face, fingerprint, iris, etc. In this thesis, various Image Quality Assessment techniques are used to detect image quality. Fake and real face images presented to biometric systems can also be detected by analyzing the image quality. In this context, No-Reference Image Quality Assessment measures such as Distortion Specific Measures (JQI, HLFI), Training Based Measure (BIQI) and Natural Scene Statistic Measure (NIQE) are implemented to analyze the quality of the face images. Three color spaces are employed to check the quality of images under various conditions. RGB, HSV and YCbCr color spaces are implemented for each of their channels separately and then the channel outputs are concatenated for each color space. The facial features are extracted using Principal Component Analysis (PCA), Local Binary Patterns (LBP) and Color Local Binary Patterns (ColorLBP) feature extraction methods for face recognition experiments. Moreover, we propose a general face recognition algorithm for low, medium and high quality face images. The experimental results are demonstrated on three publicly available face databases, namely Replay Attack, Faces94, and ColorFERET. Face recognition rates on all databases with all color spaces are presented using three aforementioned feature extraction methods. Finally, the proposed method results are demonstrated

and compared with the existing systems. The experimental results are successful and encouraging for the proposed method.

**Keywords**: Face recognition, color spaces, feature extraction, image quality assessment.

# ÖZ

Yüz tanıma sistemlerinde sahtelik riskini azalttığı için görüntü kalitesi önemlidir. Geçmiş çalışmalarda bahsedilen en yaygın yüz yanıltma saldırıları, mobil saldırı, yüksek çözünürlüklü saldırı ve baskı saldırısıdır. Bu çeşit saldırılar, biyometri araştırma topluluklarını yüz, parmakizi, iris gibi biyometrik özellikleri kullanan saldırı tehditlerine karşı harekete geçirmiştir. Bu tezde, görüntü kalitesini saptamak için Görüntü Kalitesi Değerlendirme (IQM) teknikleri kullanılmıştır. Biyometrik sistemlere sunulan sahte ve gerçek yüz resimleri de görüntü kalitesinin analiz edilmesiyle tespit edilebilir. Bu bağlamda, yüz görüntülerinin kalitesini analiz etmek için Çarpıtmaya Özel Ölçümler (JQI, HLFI), Eğitim Tabanlı Ölçüm (BIQI) ve Doğal Manzara İstatistik Ölçümü (NIQE) gibi Referanssız Görüntü Kalitesi Değerlendirme Ölçümleri uygulanmıştır. Çeşitli durumlar için, görüntü kalitesinin kontrolu üç farklı renk uzayı kullanılarak yapılmıştır. RGB, HSV ve YCbCr renk uzaylarının her bir kanalı ayrı ayrı ve daha sonra da bu kanalların çıktıları birleştirilerek uygulanmıştır. Yüz tanıma deneyleri için, öznitelik çıkarma yöntemi olarak Ana Bileşenler Analizi (PCA), Yerel İkili Örüntü (LBP) ve Renkli Yerel İkili Örüntü (ColorLBP) yaklaşımları kullanılmıştır. Ayrıca düşük, orta ve yüksek kalitedeki yüz görüntüleri için genel bir yüz tanıma algoritması önerilmiştir. Deney sonuçları, Replay Attack, Faces94 ve ColorFERET isimli üç halka açık yüz veritabanı üzerinde gösterilmiştir. Tüm veritabanları üzerinde, üç renk uzayı ve bahsedilen üç öznitelik çıkarma yöntemleri kullanılarak yüz tanıma oranları sunulmuştur. En sonunda da önerilen yöntemin sonuçları gösterilmiş ve varolan sistemlerle karşılaştırılmıştır. Önerilen yöntemle elde edilen deney sonuçları başarılı ve teşvik edicidir.

**Anahtar Kelimeler:** Yüz tanıma, renk uzayları, öznitelik çıkarma, görüntü kalitesi değerlendirme.

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| | |
|---|---|
| BIQI | Blind Image Quality Index |
| FR-IQM | Full-Reference Image Quality Measure |
| HLFI | High Low Frequency Index |
| HSV | Hue, Saturation, Value |
| IQM | Image Quality Measurement |
| JQI | Jpeg Quality Index |
| LBP | Local Binary Pattern |
| NIQE | Natural Image Quality Evaluator |
| NR-IQA | No-Reference Image Quality Assessment |
| NR-IQM | No-Reference Image Quality Measure |
| PCA | Principal Component Analysis |
| RGB | Red, Green, Blue |
| SVM | Support Vector Machine |

# Chapter 1

# INTRODUCTION

## 1.1 Face Recognition with Gray-level Images

A facial recognition method is a technology competent in recognizing or verifying a character from a digital photograph or a video frame from a video source. There are various methods in which facial recognition systems work, but in common, they work by balancing selected facial features from the given image with faces within a database. It is also defined as a Biometric Artificial Intelligence-based treatment that can uniquely recognize a character by examining patterns based on the person's facial textures and shape [1].

Grayscale images are separated from one-bit bi-tonal black-and-white photographs, which, in the setting of computer imaging, are photographed with only two colors: black and white (also described bilevel or binary images). Grayscale images have many tones of gray in between. Under such situations, recognition performance with color images is significantly more reliable than that with grayscale images. Many image processing and biometric algorithms use grayscale images for input rather than color images [2]. One essential purpose is because by transforming to grayscale, it departs the luminance plane from the chrominance planes. Luminance is also more valuable for detecting visual features in an image. For example, if it was required edges based on both luminance and chrominance, it needs further work. Grayscale images have one color channel as exposed to three in a color image (RGB, HSV and

YCbCr [3]). The internal complexity of grayscale images is lower than that of color images as you can take points relating to brightness, contrast, edges, shape, contours, textures, and perspective without color. Processing in grayscale is also much quicker. If it is assumed that processing a three-channel tone image uses three times as long as processing a grayscale image, then we can save processing time can be saved by excluding color channels that are not needed. Basically, color raises the complexity of the model and, in general, slows down processing.

## 1.2 Face Recognition with Colored Images

A face recognition algorithm for color images in the presence of changing illumination conditions as well as complex backgrounds is necessary based on a new lighting compensation technique and a nonlinear color transformation. Experimental decisions exhibit successful face recognition over a wide range of facial variations in color, position, scale, orientation, and expression in images from several photo collections [4].

The role played by color data in object recognition has been the case of much debate. Much of the theoretical modeling and empirical work in recognition has centered on shape cues. Color resembled to confer no significant recognition advantage beyond the luminance information. In interpreting these data, it has been recommended that the absence of participation of color hints to face recognition is because they do not alter form from shading methods, which are deemed to be mostly 'color-blind' [5].

## 1.3 Image Quality Metrics

The whole class of malformations that images are subject to during acquisition, processing, storage, and reproduction can demote their perceived quality. Since subjective evaluation is time-consuming, costly, and resource-intensive, objective processes of evaluation have been proposed. One type of these techniques, Image Quality Assessment (IQA) metrics, has become very common, and new metrics are proposed continuously. Advances are speedy in the imaging activity, and new and more advanced products are continuously being introduced into the market. In order to check that the new technologies originate in higher-quality images than the current technology, some kind of quality assessment is required.

Existing studies, such as the one by Wang and Bovik [6], frequently concentrate on grayscale image quality metrics, whereas the study by Avcibas et al. [6] covers only simple statistical metrics. In this thesis, both colored and grayscale image quality metrics are evaluated.

No-Reference Image Quality Assessment (NR-IQA) has no data around the reference image. General-purpose NR-IQA is used to estimate the tone of images without information about the reference images and without prior knowledge about the types of distortions in the examined image. This problem has been analyzed based on a theory that an effective combination of image features can be used to improve NR-IQA approaches having a competitive performance with the state-of-the-art.

No-Reference Image Quality Assessment measures such as Distortion Specific Measures (JQI, HLFI), Training Based Measure (BIQI) and Natural Scene Statistic Measure (NIQE) are implemented in this thesis to analyze the quality of the face images. Types of No-Reference Image Quality metrics are shown in Figure 1. Descriptions about JQI, HLFI, BIQI and NIQE image quality assessment are summarized in Table 1.

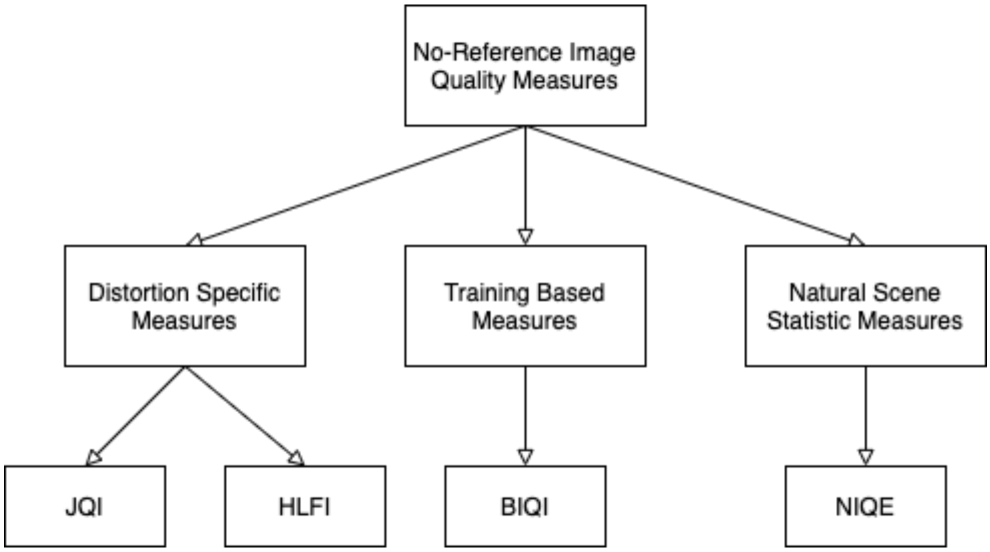


Figure 1: Types of No-Reference Image Quality Measures

Table 1: Descriptions of No-Reference Image Quality Metrics

| # | **Acronym** | **Name** | **Ref.** | **Description** |
|---|---|---|---|---|
| 1 | JQI | JPEG Quality Index | [16] | See [16] and practical implementation is available in [29]. |
| 2 | HLFI | High-Low Frequency Index | [17] | $HLFI(I) = \frac{\sum_{i=1}^{i_l}\sum_{j=1}^{j_l}\lvert F_{i,j}\rvert - \sum_{i=i_h+1}^{N}\sum_{j=j_h+1}^{M} \lvert}{\sum_{i=1}^{N}\sum_{j=1}^{M}\lvert F_{i,j}\rvert}$ |
| 3 | BIQI | Blind Image Quality Index | [18] | See [18] and practical implementation is available in [29]. |
| 4 | NIQE | Naturalness Image Quality Estimator | [22] | See [22] and practical implementation is available in [29]. |

## 1.4 Face Recognition with Different Color Spaces

The light mirrored from an object is multi-spectral and eyes recognize the object by perceiving the color spectrum of the visible light [7]. However, most of the face recognition methods had used only luminance data. Many face recognition methods transform the color input images to grayscale images by discarding the color information and use only luminance information.

Only a low number of face recognition studies using color information exist in the literature. Torres et al. proposed a global Eigen scheme to make use of color parts independently [8]. They announced a potential improvement of face recognition using color information. Rajapakse et al. proposed a non-negative matrix factorization (NMF) method to recognize color face images and designated that the color image recognition method is better than the grayscale image recognition approaches [8]. Yang et al. showed the complicated eigenface method that combines saturation and intensity elements in the information of a complex number [9].

Color images carry more visual clues than grayscale images, and the works mentioned above showed the effectiveness of color data for face recognition. However, there is a lack of study and evaluation regarding recognition performance in diverse color spaces. In this thesis, we study different color spaces for face recognition. For the evaluation of face recognition results, ColorFERET, Replay Attack and Faces94 databases are used, which include a fraction of face images with a wide variety of facial emotions and aging. Experimental results show that the use of color data gives a notable improvement in terms of the recognition rate.

Even though most digital image acquisition devices generate R, G, and B components, the RGB color space is transformed into other color spaces depending on applications. For face recognition, the eigenface analysis in the RGB domain may not be practical, because R, G, and B components are associated mainly with each other. Some literature also showed the inefficiency of face recognition in the RGB domain [9]. Therefore, we demand to find the color space that is less correlated between its elements for the improvement of face classification performance. The most useful color spaces for face recognition are searched in this thesis.

The HSV space is the well-known color space showing human visual perception, and it is composed of hue, saturation, and value [10]. The YCbCr color domain was developed for effective image compression by departing luminance (Y) and chrominance (Cb, Cr) components. This space is also known as a useful space for skin color segmentation [11].

The rest of the thesis is organized as follows. Literature review is discussed in Chapter 2. Three color spaces, namely RGB, HSV and YCbCr are described in Chapter 3. The explanations about No-Reference Quality Measures are given in Chapter 4 with the details. Chapter 5 presents the feature extraction methods used in this thesis. Our proposed method is discussed in Chapter 6. The explanations about the databases used in the experiments are given in Chapter 7 and the experimental results are demonstrated and discussed in Chapter 8. Finally, Chapter 9 concludes the thesis.

# Chapter 2

# LITERATURE REVIEW

Face recognition is studied extensively on gray images. However, there exists some face recognition research on colored images. These studies are discussed below. Additionally, Image Quality Measures are applied for face recognition in the literature. The literature review on these studies is given in the following subsections.

## 2.1 Color Face Recognition Studies

Our expressive perception of colors in the environment affects us to assume that color must be necessary for letting us understand complex scenes and, specifically, recognizing the objects internally. However, the role acted by color data in object recognition has been the subject of much debate. Significantly, the theoretical modeling and experimental work in recognition have concentrated on form cues. A hypothesis that has enjoyed enduring popularity is that objects may be encoded primarily in terms of their luminance-defined bounding-edge structure [12], with surface resources such as color and texture being of little importance. Researchers, on the other side of this discussion, have recommended models of recognition that rely significantly on color cues [12].

Some research studies dealt with the contribution of color in face recognition. A critical study in this notice was conducted. The researchers discovered that detectives were able to process quite regularly even those faces that had been suppressed to hue reversals (tasks included recognizing familiar faces or spotting variations among faces). The color looked to confer no significant recognition advantage beyond the luminance report. In interpreting these data, the researchers in [13] have recommended that the shortage of a contribution of color cues to face recognition is because they do not modify shape-from-shading processes, which are believed to be widely `color-blind'. However, another viable reason for the observed shortage of a contribution of color to face recognition in these studies is that, in circumstances where extreme shape cues are possible (as in high-resolution face images), completion may already be at the ceiling and the complement of color may not be visible. The new situation to measure would be one wherein shape cues are progressively demoted. If the color does represent a role in face recognition, its supplement would be more visible under such conditions.

In this thesis, one of the essential criteria for recognizing the face's image is its color. The three-layer color images have a coded matrix that is stored in different formats, and each of the forms has its advantages and disadvantages. However, in this thesis, we have examined three different types of coding and used them. We have done it, and, finally, a complete explanation for each of them has been provided as to which one is more appropriate. Currently, the speed of processors has changed dramatically, so we can extract a lot more detail using color images in a short time, so there's a logical way to use it.

## 2.2 Image Quality Measurement Studies on Face Recognition

Image quality assessment for biometric individuals, in particular, is a research topic, and, in most situations, the estimated quality parts are biometric modality-specific. Two classes of quality measures can be noticed: generic (can be used for any biometric modality) [14] or biometric modality-specific (composed to address problems associated with a specific modality such as fingerprints, iris, or faces).

Some examples of generic quality measures that are applied to qualify the recognized image degradation (typically, compared to a reference good quality image) are image contrast, brightness, sharpness, and illumination. Face-based quality standards, such as ISO/IEC-19794–5, include but are limited to digital formatting of face images due to resolution, and grayscale contrast; to scene departure due to illumination, head rotation, eyes open versus close, mouth open versus close, and glasses versus no glasses; and to location of the face as well as exposure, camera, image brightness, focus and sharpness [14].

Image quality metrics can be categorized according to the availability of a source image [15]: (i) Full-reference, which is the matter with most existing approaches; (ii) "Blind," or no reference-based quality assessment, which is a more expedient approach (reference images are not always available). There are various image quality measures recommended in the literature, such as High-Low Frequency Image (HLFI) [16], Blind Image Quality Indices (BIQI) [17], JPEG Quality Index (JQI) [18], and Natural Image Quality Evaluator (NIQE) face quality measure [19].

Another essential criterion for identifying a face image is image quality. The higher quality of images, the more details it has, so the more likely it is that the face image will be recognized. In this thesis, three different types of image quality are used so that we can consider an index that stabilizes the minimum image quality, which also has an optimal level of recognition. The reason for this is first to speed up the processing, and then the storage space in the computers is limited; when the number of images increases, the time cost and storage space are the main factors in optimizing the system.

# Chapter 3

# COLOR SPACES

A color space is a useful method for users to understand the color capabilities of a particular digital device or file. It represents what a camera can see, a monitor can display, or a printer can print. There are a variety of color spaces, such as RGB, YCbCr, HSV. Color space, also known as the color model (or color system), is an abstract mathematical model which simply describes the range of colors as tuples of numbers, typically as 3 or 4 values or color components.

## 3.1 RGB Color Space

RGB color space is known by holding it as all potential colors that can be obtained from three colored lights for red, green and blue. Assume, for example, lighting three lights together onto a white surface in a dim room: one red lamp, one green lamp, and one blue lamp, each with dimmers. If only the red lamp is on, the surface will be red. If only the green lamp is on, the surface will look green. If the red and green lamps are on together, the surface will look yellow. Dim the red light, and the surface will become more of a yellow-green. Dim the green light instead, and the surface will become more orange. Bringing up the blue light a bit will cause the orange to become less saturated and more whitish. In all, each set of the three dimmers will display a different result, either in color or in brightness or both [23].

Since the human optic only has color-sensitive receptors for red, green, and blue, it is theoretically feasible to decompose every visible color into sequences of these three "basic colors." Color monitors, for example, can display millions of colors easily by mixing different energies of red, green, and blue. It is most popular to place the range of intensity for all colors on a scale from 0 to 255 (one byte). The range of intensity is also recognized as the "color depth." The potentialities for mixing the three primary colors together can be depicted as a three dimensional coordinate plane with the values for red, green, and blue on each axis.

If all three color channels have a rate of zero, it means that no glow is transmitted, and the resulting color is black (on a monitor, for instance, it cannot be blacker than the outside of the monitor producing 0 light). If all three color channels are set to their maximum rates (255 at a one-byte color depth), the resulting color is white. This standard of color mixing is also described as "additive color mixing."

## 3.2 HSV Color Space

HSV is more like how people perceive color. It has three elements: hue, saturation, and value. This color range represents colors (hue or tint) in terms of their tone (saturation or amount of gray) and their brightness value.

"Hue" is the color part of the model, displayed as a number from 0 to 360 degrees: Red appears between 0 and 60 degrees. Yellow appears between 61 and 120 degrees. Green appears between 121 and 180 degrees. Cyan appears between 181 and 240 degrees. Blue appears between 241 and 300 degrees. Magenta appears between 301 and 360 degrees.

"Saturation" describes the amount of gray in a particular color, from 0 to 100 percent. Demoting this element toward zero introduces more gray and provides a faded effect. Seldom, saturation seems like a range from 0 to 1, where 0 is gray and 1 is a primary color.

“Value” acts in conjunction with saturation and describes the intensity or brightness of the color, from 0 to 100 percent, where 0 is entirely black, and 100 is the brightest and shows the most color.

### 3.3 YCbCr Color Space

YCbCr color spaces are managed by a mathematical coordinate transmutation from an associated RGB color space. If the underlying RGB color space is pure, the YCbCr color space is absolute as well. In YCbCr color space, Y is the luma element of the color. The Luma element is the brightness of the color which means the light intensity of the color. The human eye is more susceptible to this part. Cb and Cr are the blue segments and red segments related to the chroma segment. Cb is the blue segment relative to the green segment. Cr is the red segment relative to the green segment. These segments are less sensitive to human eyes [20].

The YCbCr color model was realized as part of ITU-R BT.601 during the improvement of a worldwide digital component video standard. YCbCr is a scaled and offset version of the YUV color pattern. Y is the luma segment defined to have a nominal 8-bit range of 16 – 235; Cb and Cr are the blue-difference and red-difference chroma segments sequentially, which are described to have a nominal range of 16 – 240.

In contrast to RGB, the YCbCr color space is luma-independent, resulting in a better performance. The corresponding skin cluster is given as [15]: $Y > 80$ $85 < Cb < 135$ $135 < Cr < 180$, Where Y, Cb, and Cr = [0, 255].

RGB gives better (more consistent) results and the same or brighter colors. Using RGB is one of the leading causes of colors not matching between monitor and print. RGB is the world's default color space that is used in most of the accessories.

# Chapter 4

# NO-REFERENCE IMAGE QUALITY MEASURES

NR-IQM methods require full or partial information from a reference image for visual quality assessment, whereas NR-IQM methods assess the visual quality of images without a reference. Most NR-IQM metrics predict the visual quality of images that are distorted only with a single distortion type. Four NR-IQM, namely JQI, HLFI, BIQI, and NIQE, are used in this thesis, which are described below in details.

## 4.1 JQI

JQI is the JPEG Quality Index which estimates the quality in images. These images are JPEG images affected by the usual block artifacts found in many compression algorithms.

## 4.2 HLFI

The High-Low Frequency Index (HLFI) is another no-reference quality metrics which is sensitive to the sharpness of the image. It is computes the difference between the power in the lower and upper frequencies of the Fourier Spectrum. The formula used to calculate HLFI is as follows:

$$HLFI(I) = \frac{\sum_{i=1}^{i_l}\sum_{j=1}^{j_l}|F_{i,j}| - \sum_{i=i_h+1}^{N}\sum_{j=j_h+1}^{M}|F_{i,j}|}{\sum_{i=1}^{N}\sum_{j=1}^{M}|F_{i,j}|} \tag{4.1}$$

where I is the image and Fi,j is respective Fourier transforms of image I in HLFI, jl, jh, il, ih are the indices corresponding to the lower and upper-frequency thresholds.

In the current implementation, jl = jh = 0.15 x M and il = ih = 0.15 x N where M is the number of rows and N is the number of columns.

## 4.3 BIQI

No-reference (NR) image quality assessment (IQA) refers to the design of algorithms that attempts to resolve the quality of twisted images without recourse to comparison with any reference image. Newly, many prosperous NR-IQA algorithms have been proposed. A new two-step structure for NR-IQA declared a blind image quality index (BIQI) based on natural scene statistics (NSS).

Blind IQA methods use earlier research used from natural scene alteration-free images to train the primary model. The explanation behind this aim counts on the hypothesis that clear photographs of the world naturally show specific natural properties that drop within an assured subspace of all photographs possible. If calculated correctly, deviancies from the balance of natural statistics can help to determine the perceptual quality of an image.

## 4.4 NIQE

NIQE uses a priori knowledge taken from natural scene distortion-free images to train the initial model. The Natural Image Quality Evaluator (NIQE) is an entirely blind image quality analyzer based on the construction of an aware quality collection of statistical features related to a multivariate Gaussian natural scene statistical model.

In short, by examining the above methods in general, it will pay attention to their accuracy. If some of them do not provide appropriate and citational answers, it will not use them to continue the processing. Of course, the HLFI method can be used to draw more valuable solutions from a publicly available formula. However, the range of numbers obtained for all three types of image quality and different color spaces must first be checked.

# Chapter 5

# FEATURE EXTRACTION METHODS

Feature extraction is sometimes referred to as a dimensionality reduction process, where an initial set of raw variables is reduced to more manageable groups (features) for processing, while still wholly and accurately describing the original data set. Facial feature extraction is the process of extracting face component features like eyes, nose, mouth, and etc. from human face image. Facial feature extraction is very much important for the initialization of processing techniques like face tracking, facial expression recognition or face recognition. Among all facial features, eye localization and detection is essential, from which locations of all other facial features are identified. However, the existing face recognition techniques failed to identify the exact person.

An appearance-based feature extraction method, namely, Principal Component Analysis (PCA) is used in this thesis. On the other hand, Local Binary Patterns (LBP) and Color Local Binary Patterns (ColorLBP) methods are implemented as texture-based feature extraction methods. These methods are explained below in detail.

## 5.1 PCA

PCA summarizes data from a full set of variables into fewer variables by using some sort of alteration onto them. The transformation is utilized in such a way that linearly correlated variables get changed into uncorrelated variables. Correlation tells us that there is the redundancy of data, and if this redundancy can be decreased, then information can be packed. For instance, if there are pair variables in the variable set which are highly correlated, then we are not obtaining any other data by holding both the variables because one can be nearly shown as the linear combination of the other. In such situations, PCA transfers the variance of the secondary variable onto the first variable by rotation and translation of original axes and projecting data over new axes. The area of projection is defined using eigenvalues and eigenvectors. So, the first few transformed points (termed as Principal Components) are intense in information, whereas the last features carry mostly noise with negligible data in them. This transferability lets us hold the first few principal components, thus decreasing the number of variables significantly with the least loss of data. Stages of PCA algorithm are described one by one in the following subsections.

### 5.1.1 Standardization of the data

The first stage in the PCA algorithm is to perform the standardization of the data. It is known that missing out on standardization will presumably result in a biased outcome. Standardization is all about comparing the data in such a way that all the variables and their contents lie within an analogous range.

An example related to the standardization of data can be described if there are two variables in our dataset; one has values differing between 10-100, and the other has values between 1000-5000. In such circumstances, it was evident that the production estimated by handling these predictor variables is operating to be biased since the variable with a greater area will have a more visible influence on the outcome. Hence, standardizing the data into an analogous range is essential. Standardization is carried out by deducting each variable value in the data from the mean and dividing it by the overall deviation in the dataset. It can be measured as follows:

$$Z = \frac{\text{Variable value} - \text{mean}}{\text{Standard deviation}} \tag{5.1}$$

where Z is the standardized variable, and in this way, all the variables in the data are balanced across a standard and comparable scale.

### 5.1.2 Computing the Covariance Matrix

PCA supports to identify the correlation and dependencies between the features in a dataset. A covariance matrix reveals the correlation between the diverse variables in the dataset. It is necessary to identify heavily dependent variables because they carry biased and redundant information, which decreases the overall performance of the image. Mathematically, a covariance model is a p × p matrix, where p describes the dimensions of the dataset. Each entry in the pattern describes the covariance of the identical variables. Covariance matrix (C) is calculated as follows:

$$C = ZZ^{T} \tag{5.2}$$

where Z is standardized face vector.

### 5.1.3 Calculating the Eigenvectors and Eigenvalues

Eigenvectors and eigenvalues are the mathematical constructs that are calculated from the covariance matrix to discover the principal components of the dataset. Eigenvalues, on the other hand, represent the scalars of the particular eigenvectors. Hence, eigenvectors and eigenvalues will be used to obtain the principal components of the dataset.

### 5.1.4 Computing the Principal Components

Once we have calculated the eigenvectors and eigenvalues, all we have to do is to replace them in descending index, where the eigenvector with the highest eigenvalue is the most important and thus forms the first principal component. The principal components of lesser importance can thus be excluded in order to decrease the dimensions of the data. The last step in calculating the Principal Components is to form a model known as the feature matrix that holds all the essential data variables that possess maximum information about the data.

### 5.1.5 Reducing the Dimensions of the Dataset

The final step in applying PCA is to re-arrange the primary data with the final principal components, which describes the maximum and the essential information of the dataset. The maximum number of nonzero eigenvectors that can be used is equal to the number of images minus one in the training stage. This number can be reduced if required.

## 5.2 LBP

Local Binary Patterns are among the modern texture descriptors. The original LBP descriptor replaces the value of the pixels of an image with decimal characters, which are called LBPs or LBP codes that encode the local structure around each pixel [19–21]. Each central pixel is analyzed with its eight neighbors; the neighbors having smaller content than that of the central pixel that has the bit 0, and the different neighbors having value alike to or larger than that of the central pixel will have the bit 1. For each given central pixel, one can produce a binary character that is obtained by concatenating all these binary bits in a clockwise manner, which begins from one of its top-left neighbors. The resulting decimal value of the produced binary number renews the central pixel value. The histogram of LBP tags (the frequency of appearance of each code) determined over a field or an image can be worked as a texture descriptor of that image.

### 5.2.1 Training with the Algorithm

First, the algorithm should be used for training. To do so, we require to use a dataset with the facial images of the people we want to recognize. We require to set an ID (it may be a character or the name of the person) for each image, so the algorithm will apply this data to recognize an input image and then give an output. Images of the same person must have the same ID.

### 5.2.2 Applying the LBP Operation

The first computational level of the LBP is to build a central image that illustrates the original image in a better way by highlighting the facial components. To do so, the algorithm uses a theory of a sliding window based on the parameters such as radius and adjacency. Figure 1 shows LBP procedure on a face image.

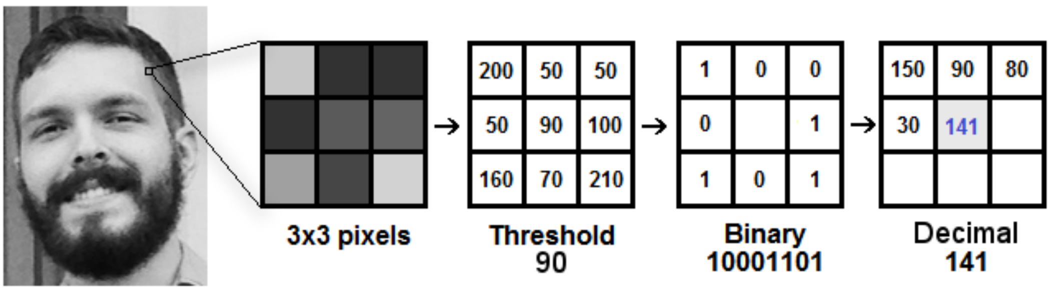


Figure 2: LBP procedure.

Based on the image in Figure 2, LBP can be described as follows. Suppose we have a facial image in grayscale. We can get a section of this image as a window of 3x3 pixels. It can also be described as a 3x3 matrix, including the intensity of each pixel (0~255). Then, we require to catch the central value of the matrix to be applied as the threshold. This value will be applied to set the new values from the eight neighbors. For each neighbor of the central-value (threshold), a new binary value is initiated. We set 1 for values similar to or higher than the threshold and 0 for values below the threshold. Now, the matrix will carry only binary values (ignoring the central value).

We had to concatenate each binary value from each location from the matrix line by line into a different binary value (e.g., 10001101). Then, we transform this binary value to a decimal value and fix it to the central value of the matrix, which is genuinely a pixel from the original image. At the end of this LBP procedure, we have a new model that represents better the characteristics of the original image. Figure 2 shows possible number of adjacent blocks that can be selected.

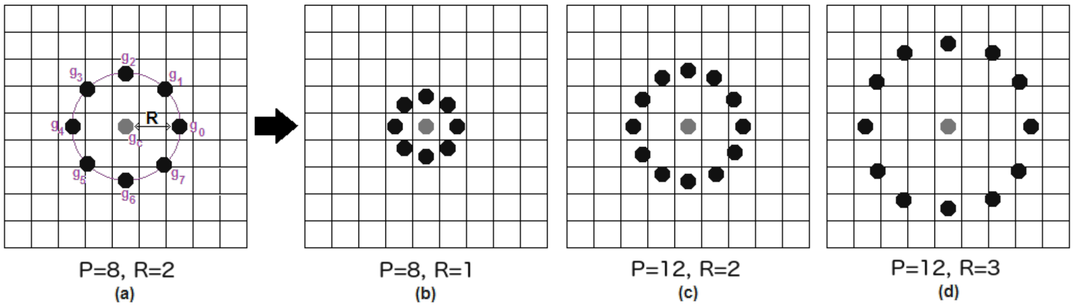


Figure 3: Model of LBP transformation pixels.

### 5.2.3 Extracting the Histograms

Using the model created in LBP feature extraction for each pixel as shown in Figure 3, the image can be split into multiple grids as shown in Figure 4.

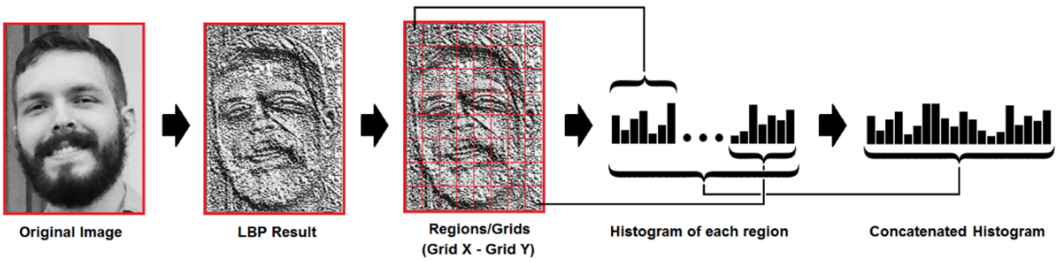


Figure 4: LBP process diagrams and histograms

Based on the image in Figure 4, the histogram of each region can be obtained as follows: Since the image is in grayscale, each histogram (from each grid) will carry only 256 positions (0~255) serving the occurrences of any pixel intensity. Then, it is required to concatenate each histogram to generate a new and larger histogram. Assuming we have 8x8 grids, we will have 8x8x256=16,384 points in the concluding histogram. The last histogram depicts the characteristics of the original image.

### 5.2.4 Performing the Face Recognition

In the recognition stage, the algorithm is assumed to be previously trained. Each histogram built is used to draw each model from the training dataset. So, given an input (test) image, we complete the steps again for this new image and create a histogram that represents the image. So, to find the model that matches the input image, we just require to match two histograms (features) and to return the image with the most resembling histogram. We can use different distance measures to compare the histograms (calculate the distance between two histograms), for example, Euclidean distance, chi-square, absolute value, etc. In this thesis, Manhattan distance is used.

The output of the algorithm is the ID from the model with the closest histogram. The algorithm should also return the computed distance, which can be used as a 'confidence' measurement. We can then apply a threshold and the 'confidence' to automatically determine if the algorithm has accurately recognized the image. We can assume that the algorithm has strongly recognized if the confidence is lower than the threshold defined.

## 5.3 ColorLBP

The third feature extraction method used in this thesis is ColorLBP. A color photograph includes three component images. The generally used color space is the RGB color space. To decrease the sensation of the RGB photographs to varying image circumstances, the RGB color space is represented by normalizing the R, G and B elements. On the other hand, the HSV color space is induced by the human visual system. Hue and saturation represent chrominance, while power or value specifies luminance [23]. In YCbCr color space, Cb, Cr and Y components exist where the RGB parts are divided into luminance, chrominance blue, and chrominance red. The same steps apply to the HSV color space. Each channel is processed separately, and eventually, their histograms are summarized.

ColorLBP feature extraction method applies LBP feature extraction on each channel of a specific color space. The features extracted from each channel are then concatenated in order to obtain the final feature vector. The details related to the stages of ColorLBP are explained in the following subsections.

**5.3.1 Computation of channel-wise color LBP histograms**

ColorLBP method uses LBP operator by combining the features of each color channel. Let *i* be a red-green-blue (RGB) color face image with size Nh in Nw pixels. In order to obtain the channel-wise color LBP histograms of *i*, we obtain $i'$ with the image having different color representations (e.g., an RGB color image is converted into a YCbCr color image). Then, a total of K separate color component images resulting from color space transformation are created (e.g., luminance (Y) or chrominance component (Cb or Cr) images in the YCbCr color space). Then, let S(i) be the $i^{th}$ color part model produced after the color space transformation. Finally, a gray level LBP histogram is individually and independently calculated from each corresponding color component image (S(i)).

Moreover, in the calculation of the color LBP histogram, a uniform LBP operator is selected because a typical face model includes only a small number of LBP values which is called a uniform pattern [24].

# Chapter 6

# PROPOSED METHOD

## 6.1 The Algorithm of the Proposed Method

A standard method for low quality, medium quality and high quality color images is proposed in this thesis. According to the face recognition experiments with different color spaces and several feature extraction methods, we propose a standard method for a general color face recognition system.

The algorithm of the proposed method is given below:

1) Read the training images.
2) Apply ColorLBP feature extraction method with RGB, HSV and YCbCr color spaces separately. Three possibilities are calculated in this step, but only one of them will be used in the testing part according to the type of test image.
3) Read the test image.
4) Check image quality of the test image by calculating HLFI value.
5) Decide the quality type of the test image as low, medium, or high-quality image.
6) If the test image quality is low, apply feature extraction with ColorLBP method in HSV color space.
7) If the test image quality is medium, apply feature extraction with ColorLBP method in RGB color space.

8) If the test image quality is high, apply feature extraction with ColorLBP method in YCbCr color space.
9) Perform matching using Manhattan Distance measurement and classification using the Nearest Neighbor classifier between test image features and the same type of training image feature sets using the same color space.
10) Construct the decision (ID) of the system.

The block diagram of the proposed method is given in Fig 5.

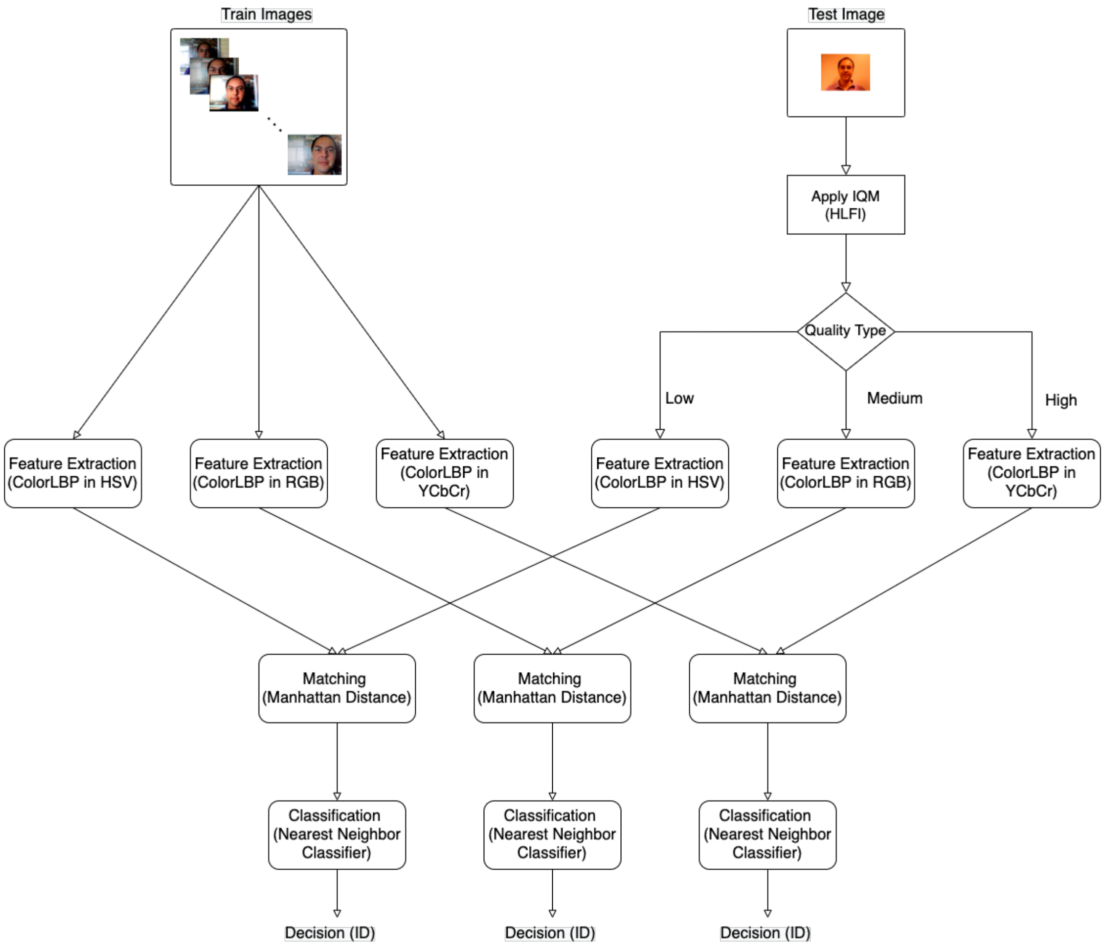


Figure 5: Proposed method flowchart

Each stage of the proposed method is described in the following sections in detail.

## 6.2 Application of IQM Method

After reading the color face images, No-reference Image Quality Assessment method, namely HLFI method, is applied on the image to check its quality type. Using the average HLFI method on train images, we find a threshold to identify the quality of each image and then classify them as low-quality, medium-quality, and high-quality categories.

## 6.3 Feature Extraction

Feature extraction of the proposed method involves the usage of ColorLBP feature extraction method. ColorLBP is used with three color spaces namely RGB, HSV and YCbCr. First of all, the images are read in RGB mode and separated into green, blue and red channels. Then the features are extracted for each channel separately using ColorLBP method. For the HSV color space, all the images are converted into HSV format, then each image's H, S and V channels are separated. Afterwards, the features for each channel are extracted using the aforementioned ColorLBP method. The same process is performed for the YCbCr color space.

In order to apply ColorLBP algorithm, the first step is to extract the features in each color channel separately in a color space and then concatenate the features extracted from each channel to obtain the final feature set. Specifically, for RGB color space, Red channel features are extracted first, then Green channel features are extracted and finally Blue channel features are obtained. All these three set of features are then concatenated to obtain RGB color space features. This process is repeated for HSV and YCbCr color spaces to extract the feature sets on these color spaces. Therefore, ColorLBP algorithm is implemented in RGB, HSV and YCbCr color spaces separately.

On the other hand, test images are read and HLFI method is applied on them to find the image quality type. If the test image quality is low, then ColorLBP feature extraction method is applied on it using HSV color space. If the test image quality is medium, RGB color space is used with ColorLBP feature extraction method. If the quality of the test image is high, then YCbCr color space is applied with ColorLBP algorithm to extract the test image features.

The quality of the test image should be analyzed to get the best decision after matching. In this way, the most appropriate color space is used for feature extraction. The reason for this is that any kind of coding on colors causes in some cases to increase the recognition error, especially in the corners. The best-performing algorithm to identify each test image is to be chosen. In this study, ColorLBP feature extraction method is the most appropriate method for all types of images. However, for each type of image quality, different color spaces perform in a different way. For example, HSV color space achieves the best results for low quality images, RGB is the most appropriate for medium quality images and YCbCr color space is the best choice for high quality images. Therefore, the aforementioned color spaces are implemented for different quality images in the proposed method.

## 6.4 Matching and Classification

Matching is performed using Manhattan distance measure. The distance between two feature vectors are calculated using Manhattan distance as follows:

$$|\mathrm{A}-\mathrm{B}| = \sum_{i=1}^{d} |a_i - b_i| \tag{5.2}$$

where A and B are two feature vectors to be matched, $a_i$ and $b_i$ are the values of the feature vectors and d is the length of the feature vectors.

On the other hand, Nearest Neighbor classifier is used for classification which manages high performance under multiple techniques of statistical patterns controlled. Typically, the Nearest Neighbor needs both authentic and fake case training. By determining the distance from the nearest case of training, a new sample is categorized; the sign at that point determines the sample classification. By taking the nearest k points and allocating the majority mark, the Nearest Neighbor classifier extends this concept. Due to the validation (input test set), the n-dimensional n characteristic pattern vector can be calculated using the samples of training and classified to the minimum distance type. The training examples include vectors with a class label described. In the closest neighbor classification training stage, the vectors are stored, and class labels are assigned to training examples. The Nearest Neighbor classifier is applied to the concatenated feature vector obtained from the feature-level fusion phase. After applying the Nearest Neighbor classifier, the face image is classified.

The Nearest Neighbor classifier is used in classifying the face image. A face image is classified by the number of votes of its neighbors. Then the face image is assigned to the most resembling one among its nearest neighbors. Therefore, the most resembling face identity (id) among the training images is selected as the decision of the system. This decision is counted to be correct if the id of the test image is exactly the same as the id of the decision of the system.

# Chapter 7

# DATABASES

Three different face image databases are used in this thesis. Replay Attack database which includes real and fake color face images, Faces94 database with color face images and ColorFERET database. All of the images in the aforementioned databases are colored images however their quality levels are different. The details related to each database are given in the following subsections.

## 7.1 Replay-Attack Database

Replay-Attack is a database of face videos obtained from Idiap [19]. The Replay Attack Database for face spoofing consists of 1300 video-clips of image and movie attack attempts to 50 patients, supporting different illumination conditions. All videos are produced by either having a (real) customer trying to reach a laptop within a built-in webcam or by presenting an image or a video recording of the same customer for at least 9 seconds. The webcam creates color videos with a resolution of 320 pixels (width) by 240 pixels (height). The movies were filmed on a MacBook laptop using the QuickTime framework (codec: Motion JPEG) and stored into ".mov" files. The frame rate is about 25 Hz. Besides the primary support on Apple machines, these records are merely readable using MPlayer, FFmpeg or any different video utilities accessible under Linux or MS Windows systems.

Real client accesses, as well as data gathered for the attacks, are taken under two different illumination situations:

1) Controlled: The office lamp was turned on, curtains are down, and the environment is unvaried;
2) Adverse: The curtains are up, more complicated framework, office lamps are off.

To design the attacks, high-resolution images and movies from each person were recorded under the same conditions as in their authentication sessions, using a Canon PowerShot SX150 IS camera, which records both 12.1 Mpixel photos and 720p high-definition movies. The way to complete the attacks can be classified into two subsets: the first subset includes videos generated using a stand to operate the client biometry ("fixed"). For the following set, the attacker holds the devices used for the attack with their own hands. In this database, we have 100 real images, 50 of which have been used for testing and 50 for training. There are three different types of attacks. Each type of attack is identified as High-def, Mobile Attack and Print Attack, respectively. According to the above attack types, the first attack with high-quality images was shown on the tablet. The second type is showing the image on the mobile screen in front of the camera, and the last one is printing the image and showing it to the camera. All types of attacks are made up of 100 images, 50 of which have been selected for testing and the other 50 for training. Figure 6 shows sample images of the Replay Attack database.

Figure 6: Sample images of Replay Attack database

## 7.2 Faces 94 Database

The Face94 database [20] includes 153 subjects, each with a resolution of 180x200 pixel, and the database comprises images of male and female individuals in separate indexes (20 females, 113 males, and 20 male staffs). The photographs are mainly from first-year undergraduate students. The majority of the people are between 18 and 20 years old. The illumination is unnatural, and some of the images are taken with glasses and a mixture of tungsten and fluorescent overhead. Figure 7 shows sample images of the Faces94 database.

Figure 7: Sample images of Faces94 database

## 7.3 ColorFERET Database

ColorFERET database [21] includes 11,338 color images of size 512 × 768 pixels taken in a semi-controlled background with 13 different postures from 994 subjects.

To benchmark robustness of low points upon pose variations, we use the standard frontal image set (Fa subset) for training with one frontal image per subject. The network is then tested on one frontal pose (Fb subset). Nonetheless, the results can be further enhanced by using pose normalization approaches, which have already been found beneficial for face recognition [26, 27]. Figure 8 shows sample images of the ColorFERET database.

Figure 8: Sample images of ColorFERET database

A summary of the number of images used in the experiments from the aforementioned databases is given in Table 2.

Table 2: Summary of Number of Images Used in the Experiments

<table>
<tr><th>Dataset</th><th colspan="3">Number of train images</th><th colspan="3">Number of test images</th></tr>
<tr><td rowspan="3">Replay Attack</td><td colspan="3">50 real images</td><td colspan="3">50 real images</td></tr>
<tr><td colspan="3">150 fake images</td><td colspan="3">150 fake images</td></tr>
<tr><td>50 High-def</td><td>50 Mobile Attack</td><td>50 Print Attack</td><td>50 High-def</td><td>50 Mobile Attack</td><td>50 Print Attack</td></tr>
<tr><td>Faces94</td><td colspan="3">1520 real images</td><td colspan="3">1520 real images</td></tr>
<tr><td>ColorFERET</td><td colspan="3">268 real images</td><td colspan="3">268 real images</td></tr>
</table>

# Chapter 8

# EXPERIMENTAL RESULTS

Several experiments are conducted in this thesis on face recognition used colored images. The quality level of the images is measured using No-Reference IQM methods. Four different IQM methods are implemented and the most appropriate method is then selected to be used in the decision of image quality type. Three different color spaces namely RGB, HSV and YCbCr are employed and additionally three different feature extraction methods namely PCA, LBP and ColorLBP are used in the experiments. Several face recognition experiments are presented in the following subsections.

The experiments were conducted using a Windows 10 professional OS with 16 GB RAM and core i7 CPU @4.3 GHz.

## 8.1 No-Reference IQM Results

Four No-Reference IQM methods are implemented on each dataset in order to detect the image type whether it is high quality, low quality or medium quality image. The results for each dataset are given in the following subsections.

### 8.1.1 No-Reference IQM results on Replay Attack Dataset

Table 3 shows the experimental results of NR-IQM methods on Replay Attack dataset in RGB color space. The results are demonstrated for each subset of the dataset separately.

Table 3: Average No-Reference IQM Results using RGB on Replay Attack dataset

| Dataset | JQI | HLFI | BIQI | NIQE |
|---|---|---|---|---|
| Real Images | 7.70 | 8271132.84 | 27.23 | 2.44 |
| Highdef | 7.64 | 9191549.95 | 26.74 | 2.61 |
| Mobile | 7.69 | 10565951.74 | 38.14 | 3.00 |
| Print | 8.33 | 8966469.80 | 32.62 | 2.25 |
| All Datasets | 7.84 | 9248776.08 | 31.18 | 2.57 |

The results are obtained on Replay Attack dataset which contains medium quality images. RGB color based images have better results with HLFI method with an extensive range between image types compared to other No-Reference IQM method ranges. Therefore, HLFI is an appropriate method to estimate the image quality type in this kind of scenario.

On the other hand, Table 4 shows the experimental results of NR-IQM measurements on Replay Attack dataset in HSV color space.

Table 4: Average No-Reference IQM Results using HSV on Replay Attack dataset

| Dataset | JQI | HLFI | BIQI | NIQE |
|---|---|---|---|---|
| Real Images | 17.57 | 35398.87 | 27.35 | 3.94 |
| Highdef | 17.36 | 32722.45 | 26.92 | 4.29 |
| Mobile | 17.82 | 36521.13 | 30.11 | 4.17 |
| Print | 18.50 | 30806.30 | 28.80 | 3.44 |
| All Datasets | 17.81 | 33862.18 | 28.29 | 3.96 |

The results on Replay Attack dataset are based on medium quality images scenario. HSV color based images have better results in the HLFI method with a vast range between image types. HLFI is also an appropriate method to decide on the image quality on HSV color space.

Moreover, Table 5 shows the experimental results of NR-IQM measurements on Replay Attack dataset in the YCbCr color space.

Table 5: No-Reference IQM Results using YCbCr on Replay Attack dataset

| Dataset | JQI | HLFI | BIQI | NIQE |
|---|---|---|---|---|
| Real Images | 7.74 | 5993760.03 | 36.77 | 4.21 |
| Highdef | 8.20 | 6101433.80 | 37.01 | 4.52 |
| Mobile | 8.29 | 6660354.29 | 41.83 | 4.32 |
| Print | 8.33 | 6087265.60 | 43.32 | 4.08 |
| All Datasets | 8.14 | 6210703.43 | 39.73 | 4.28 |

The results on Replay Attack dataset are based on medium quality images scenario. YCbCr color based images have better results in the HLFI method with a broad range between image types, and HLFI is an appropriate method for this kind of scenario on YCbCr color space.

Finally, the HLFI method is selected to measure the quality of the images because the probability of incorrectly placing the image in another class is very low.

### 8.1.2 No-Reference IQM Results on Faces 94 Dataset

NR-IQM results on three color spaces are calculated in this set of experiments. Table 6 shows the average No-Reference IQM results for images for Faces94 dataset in different color spaces separately.

Table 6: Average No-Reference IQM Results on Faces94 dataset

| Color Space | JQI | HLFI | BIQI | NIQE |
|---|---|---|---|---|
| RGB | 8.76 | 2982913.14 | 32.54 | 3.27 |
| HSV | 19.15 | 13629.71 | 36.76 | 4.25 |
| YCbCr | 8.87 | 2483901.57 | 47.97 | 4.73 |

The results obtained by NR-IQM methods on Faces 94 dataset are based on different color spaces. The range of results helps us determine which color space can be the most appropriate choice for each method.

### 8.1.3 No-Reference IQM Results on Color Feret Dataset

In this set of experiments, average No-Reference IQM results on the images of ColorFERET dataset in different color spaces are presented separately. The results are shown in Table 7.

Table 7: Average No-Reference IQM Results on ColorFERET dataset

| Color Space | JQI | HLFI | BIQI | NIQE |
|---|---|---|---|---|
| RGB | 10.97 | 49998026.51 | 29.69 | 3.36 |
| HSV | 11.37 | 17199617.13 | 30.12 | 3.71 |
| YCbCr | 12.61 | 33056379.03 | 49.35 | 3.71 |

The results achieved on ColorFERET dataset are based on different color spaces. The range of results helps us determine which color space can be the most appropriate choice for each method.

## 8.2 Detailed HLFI Results

The detailed results on the Replay Attack dataset based on the different types of images using minimum, average and maximum HLFI values are shown in Table 8. The range of results helps us determine the most appropriate threshold value for each method.

Table 8: Average No-Reference IQM Results on Replay Attack dataset

| Color Space | Min HLFI | Avg HLFI | Max HLFI |
|---|---|---|---|
| RGB | 4,579,464.09 | 9,248,776.08 | 12,447,122.75 |
| HSV | 11,081.98 | 32,722.45 | 47,815.82 |
| YCbCr | 4,557,567.46 | 6,101,433.80 | 10,574,129.81 |

On the other hand, Table 9 shows average No-Reference IQM results for real images using RGB on Faces94 dataset. The results on Faces 94 dataset are based on low-quality images scenario. The range of results helps us determine the most appropriate threshold.

Table 9: Average No-Reference IQM Results on Faces94 dataset

| Color Space | Min HLFI | Avg HLFI | Max HLFI |
|---|---|---|---|
| RGB | 765,601.28 | 2,982,913.14 | 4,732,249.35 |
| HSV | 4,965.12 | 13,629.71 | 21,547.86 |
| YCbCr | 1,190,652.86 | 2,483,901.57 | 3,899,409.50 |

Table 10 shows average No-Reference IQM Results for real images using RGB on ColorFERET dataset. The results on ColorFERET dataset are based on high-quality images scenario. The range of results helps us determine which threshold can be the most appropriate for each image quality type.

Table 10: Average No-Reference IQM Results on ColorFERET dataset

| Color Space | Min HLFI | Avg HLFI | Max HLFI |
|---|---|---|---|
| RGB | 16,346,738.50 | 49,998,026.51 | 73,847,762.30 |
| HSV | 3,865,572.31 | 17199617.13 | 26649638.64 |
| YCbCr | 23,206,643.2 | 33,056,379.03 | 65,881,402.81 |

Table 11 shows the HLFI thresholds for each type of image quality on each database with minimum (MIN), average (AVG) and maximum (MAX) values.

Table 11: HLFI Thresholds

| Color Space | Low Quality (Face94) | | | Medium Quality (Replay Attack) | | | High Quality (ColorFERET) | | |
|---|---|---|---|---|---|---|---|---|---|
| | **MIN** | **AVG** | **MAX** | **MIN** | **AVG** | **MAX** | **MIN** | **AVG** | **MAX** |
| **RGB** | 765k | 2M | 73M | 2-6M | 8-10M | 11-13 | 16M | 49M | 73M |
| **HSV** | 4k | 13K | 21k | 7-14K | 30-36k | 45-58K | 3M | 17M | 26M |
| **YCbCr** | 1M | 2M | 3M | 3-4M | 5-6M | 9-11M | 2M | 33M | 65M |

As it can be seen from Table 11, in low-quality images, the color environment of the YCbCr has a more regular alternation. Also, in the quality of the average images, HSV has more stable relativity, and in high-quality images, the RGB is better preserved.

## 8.3 Face Recognition Results

The structure of the face recognition classifier allows achieving high image processing speed due to the fast background rejection and paying more attention to the face-like regions. On the other hand, the presence of information about skin color potentially can increase the efficiency of the face recognition process as it restricts the area of faces searching. As a result, it will reduce the number of false positive detections as well as the processing time of the input image. In this set of experiments, face recognition is measures using recognition rate which is calculated as follows:

$$Recognition\, rate(\%) = \frac{\text{Number of correctly recognized test images}}{\text{Total number of test images}} X100 \quad (8.1)$$

### 8.3.1 Face Recognition Results using Gray Images

Gray images are used in these set of experiments to demonstrate the face recognition results. Table 12 and 13 show face recognition results on gray images by using PCA and LBP on all datasets with gray face images, respectively. The results achieved on several datasets based on PCA and LBP feature extraction methods are presented.

The range of results helps us determine which method can be the most appropriate for each dataset.

Table 12: Face recognition results on gray images using PCA

| **Dataset** | **Number of Face Images** | **Recognition Rate (%)** |
|---|---|---|
| Replay Attack | 100 real images<br>300 fake images | 19.00 |
| Faces 94 | 2040 real images | 99.53 |
| ColorFERET | 536 real images | 61.19 |

Table 13: Face recognition results on gray images using LBP

| **Dataset** | **Number of Face Images** | **Recognition Rate (%)** |
|---|---|---|
| Replay Attack | 100 real images<br>300 fake images | 30.00 |
| Faces 94 | 2040 real images | 99.86 |
| ColorFERET | 536 real images | 50.37 |

### 8.3.2 Face Recognition Results using Colored Images

The next set of experiments are conducted on colored face images. In this respect, RGB, HSV and YCbCr color spaces are used to present face recognition results on different color spaces. Table 14 and 15 show face recognition results on colored images using LBP and Color LBP methods on all datasets, respectively. The results are given in terms of recognition rates. The range of results helps us determine which color space can be the most appropriate for each dataset.

Table 14: Face recognition results on colored images using LBP

| Dataset | Number of Face Images | Recognition Rate (%) | | |
|---|---|---|---|---|
| | | RGB | HSV | YCbCr |
| Replay Attack | 100 real images<br>300 fake images | 30 | 23 | 28 |
| Faces 94 | 2040 real images | 99.86 | 99.86 | 99.86 |
| Color Feret | 536 real images | 52.98 | 57.46 | 52.61 |

Table 15: Face recognition results on colored images using ColorLBP

| Dataset | Number of Face Images | Recognition Rate (%) | | |
|---|---|---|---|---|
| | | RGB | HSV | YCbCr |
| Replay Attack | 100 real images<br>300 fake images | 63 | 55 | 54 |
| Faces 94 | 2040 real images | 84.67 | 99.60 | 99.86 |
| Color Feret | 536 real images | 83.20 | 92.91 | 88.80 |

A summary of experimental results using three different feature extraction methods for face recognition is shown in Table 16. The best results are demonstrated for both gray and colored images. PCA works only on gray images and the best results for gray images are achieved by PCA. However, LBP works on both gray and colored images. ColorLBP method only works on colored images and it achieves the best results on colored images. A summary of the best results are shown in Table 16.

Table 16: Face recognition results

| Dataset | Number of Face Images | Recognition Rate (%) | | |
|---|---|---|---|---|
| | | **PCA** | **LBP** | **Color LBP** |
| Replay Attack | 100 real images<br>300 fake images | 19<br>(gray) | 30<br>(RGB) | 63<br>(RGB) |
| Faces 94 | 2040 real images | 99.53<br>(gray) | 99.86<br>(YCbCr) | 99.86<br>(YCbCr) |
| Color Feret | 536 real images | 61.19<br>(gray) | 57.46<br>(HSV) | 92.91<br>(HSV) |

In conclusion, Color LBP performs better in every scenario on three datasets, while LBP works well in some scenarios.

## 8.4 Proposed Method Results and Comparison with the State-of-the-art Methods

Several experiments using the proposed method and comparison of the proposed method results with the results of the existing methods on Replay Attack, Faces94 and ColorFERET databases are presented in this subsection.

### 8.4.1 Proposed Method Results on Three Databases

Experiments on the proposed method are demonstrated in this subsection. The results are presented for each database separately. Table 16 shows face recognition results with proposed method on Replay Attack database.

Table 17: Face Recognition Results with Proposed Method on Replay Attack Dataset

| **Experimental Setup** | **Recognition Rate (%)** | | |
|---|---|---|---|
| | High-def dataset | Mobile dataset | Print dataset |
| 2 Train(RR)- 2 Test(FF) | 63 | 41 | 24 |
| 2 Train(RF)- 2 Test(RF) | 55 | 54 | 43 |
| 2 Train(FF)- 2 Test(RR) | 52 | 23 | 27 |
| All datasets with 2 Train (RF) - 2 Test (RF) | 50 | | |

The results achieved on Replay Attack dataset are not very high since the images in Replay Attack database are medium quality images including real and fake images. On the other hand, Table 18 shows face recognition results with proposed method on Faces94 database.

Table 18: Face Recognition Results with Proposed Method on Faces94 Dataset

| Experimental Setup | Recognition Rate |
|---|---|
| 2 Train (10%) - 18 Test (90%) | 93.49 |
| 3 Train (15%) - 17 Test (85%) | 94.51 |
| 4 Train (20%) - 16 Test (80%) | 98.10 |
| 5 Train (25%) - 15 Test (75%) | 98.85 |
| 10 Train (50%) - 10 Test (50%) | 99.86 |

The results achieved on Faces 94 dataset are very high since all the images are low-quality images taken in controlled conditions in the database. Additionally, Table 19 shows face recognition results with proposed method on ColorFERET database.

Table 19: Face Recognition Results with Proposed Method on ColorFERET Dataset

| Experimental Setup | Recognition Rate |
|---|---|
| 1 Train (50%) - 1 Test (50%) | 92.91 |

The results achieved on ColorFERET dataset are satisfactory since the facial images in the database are high-quality images taken under controlled conditions.

### 8.4.2 Comparison with the state-of-the-art methods

The proposed method is compared with the best existing state-of-the-art methods implemented in this thesis on three databases. Table 20 presents the comparison results including the proposed method and the systems using PCA, LBP and ColorLBP feature extraction methods.

Table 20: Comparison of All Face Recognition Results

| **Dataset** | **Number of Face Images** | **Experimental Setup** | **Recognition Rate (%)** | | | |
|---|---|---|---|---|---|---|
| | | | **PCA** | **LBP** | **Color LBP** | **Proposed Method** |
| Replay Attack | 100 real images 300 fake images | All datasets with 2 Train (RF) - 2 Test (RF) | 19 | 30 | 63 | 50 |
| Faces 94 | 2040 real images | 10 Train (50%) - 10 Test (50%) | 99.53 | 99.86 | 99.86 | 99.86 |
| Color Feret | 536 real images | 1 Train (50%) - 1 Test (50%) | 61.19 | 57.46 | 92.91 | 92.91 |

The results of the proposed method on face recognition are successful and encouraging compared to the existing systems implemented in this thesis.

# Chapter 9

# CONCLUSION

In today's technological era, efficient, fast, robust, and invulnerable biometric systems are needed in order to secure personal information or physical property. Most commonly, intruders in traditional access control systems have taken the advantages of a fundamental vulnerability. Biometric authentication systems have been able to overcome the majority of traditional security systems' weaknesses/vulnerabilities and have become increasingly significant in recent years. The task of securing vital and sensitive data or information is becoming difficult and has gained popularity in the biometric research field. In this context, robust and secure face recognition is a vital issue in the biometric research field.

In this thesis, No-Reference Image Quality Assessment techniques are used to analyze image quality as low, medium or high quality. Feature extraction methods namely PCA, LBP, and ColorLBP are used to extract features of gray and colored images from different face databases. Experiments are conducted using RGB, HSV and YCbCr color spaces on three face databases namely Replay Attack, Faces94 and ColorFERET databases. The experimental results show that ColorLBP is the most appropriate method for all conditions for colored images. More specifically, HSV color space is the most appropriate for low quality images; RGB color space performs better for medium quality images and YCbCr color space is the most successful for high quality images. Therefore, the proposed method uses these conclusions and combined them into a general algorithm. The results of the proposed method are successful and encouraging compared to the results of the existing state-of-the-art face recognition methods implemented in this thesis.

As future work, an improved face recognition algorithm will be studied using different and powerful feature extraction methods and other color spaces will be studied. The combination of different color spaces will be searched for face recognition. Additionally, texture-based or deep learning based techniques can be involved further to build an enhanced face recognition system.

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