

UNIVERSITY OF GHANA, LEGON
SCHOOL OF BASIC AND APPLIED SCIENCE
DEPARTMENT OF STATISTICS & ACTUARIAL SCIENCE



UNIVERSITY OF GHANA

STATISTICAL ASSESSMENT OF THE PERFORMANCE OF
DWT-PCA/SVD RECOGNITION ALGORITHM ON
RECONSTRUCTED FRONTAL FACE IMAGES

BY

BERNARD OBO ESSAH

(10701978)

NOVEMBER, 2020

UNIVERSITY OF GHANA, LEGON
SCHOOL OF BASIC AND APPLIED SCIENCE
DEPARTMENT OF STATISTICS & ACTUARIAL SCIENCE



UNIVERSITY OF GHANA

STATISTICAL ASSESSMENT OF THE PERFORMANCE OF
DWT-PCA/SVD RECOGNITION ALGORITHM ON
RECONSTRUCTED FRONTAL FACE IMAGES

BY

BERNARD OBO ESSAH

(10701978)

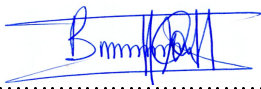
THIS THESIS IS SUBMITTED TO THE SCHOOL OF GRADUATE
STUDIES, UNIVERSITY OF GHANA IN PARTIAL FULFILMENT OF
THE REQUIREMENT FOR THE AWARD OF THE MASTER OF
PHILOSOPHY DEGREE IN STATISTICS.

NOVEMBER, 2020

Declaration Students' Declaration

I hereby declare that this thesis work is as result of my own personal effort toward the award of Master of Philosophy Degree (MPhil.) and to the best of my knowledge, it contains no material previously published by another person nor material which has been accepted for the award of any other degree of this university or any other universities except where due acknowledgement has been made in the text.

Bernard Obo Essah
Student ID (10701978)



.....
(Signature)

...15/06/2021.....
(Date)

Supervisors' Certification

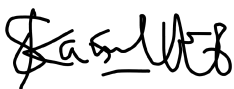
I hereby declare that the preparation and presentation of this thesis work was supervised in accordance with the guidelines of supervision on thesis laid down by the University of Ghana.

Certified by:
Dr. Louis Asiedu
(Principal Supervisor) (Signature)


.....


....15-06-2021..
(Date)

Certified by:
Dr. Samuel Iddi
(Co-Supervisor)


.....
(Signature)

15/06/2021
.....
(Date)

Certified by:
Professor Doku-Amponsah
(Head of Department)


.....
(Signature)

....15/06/21.....
(Date)

Dedication

This project work is dedicated to the Almighty God for His love, care, strength and wisdom throughout our studies of this program. Also, my special regards go to my supervisor Dr. Louis Asiedu for his time and effect to make this work a success. I also dedicate it to my parents and siblings especially my twin brother Benneth Obo Essah for his wonderful and beautiful unflinching love he shown to me toward the award of this degree.

Acknowledgment

I wish to express my sincere thanks to the Almighty God, for his protection, guidance and mercy given to me throughout my study and research work in the University of Ghana. Also, I express my profound gratitude to Dr. Louis Asiedu, my supervisor, for his numerous advice, valuable suggestions and criticism, which proved vital. In fact, his commitment and passion made it easier for the successful completion of the thesis. I acknowledge also my co-supervisor Dr. Samuel Iddi for his comments and deep vital contribution made toward the completion of the thesis. A deep thanks goes to my twin brother Benneth Obo Essah for his massive supports he shown to me toward the award of this degree. I wish the above-mentioned groups and personalities, the blessing of the Almighty God. May the Good Lord bless you all for your efforts and contributions. Finally, all my friends and colleagues, as well as all other persons who helped in one way or another toward the successful completion of this thesis, are all acknowledge for their care and support.

Abbreviations

MIT	Massachusetts Institute of Technology
JAFFE	Japanese Female Facial Expression
ICA	Independent Component Analysis
PCA	Principal Component Analysis
SVD	Singular Value Decomposition
DWT	Discrete Wavelet Transformation
FFT	Fast Fourier Transform

Abstract

Face recognition is the second most important biometric part of the human body, apart from the biometric finger print. Detecting and measuring half face image processing or pattern recognition is a challenge in this field. The research made use of Discrete Wavelet Transform (DWT) as the preprocessing mechanism and adopted the Principal Component Analysis and Singular Value Decomposition (PCA/SVD) for feature extraction and recognition. Numerical assessment of the performance of the adopted recognition algorithm gave average recognition rates of 95% and 75% when left and right reconstructed face images are used for recognition. Statistical analysis using the Wilcoxon Sign Rank test shows that, there is no significant difference in the left and right reconstructed half face images when DWT-PCA/SVD is used for recognition. In conclusion, DWT-PCA/SVD is therefore recommend as one of the best noise viable algorithm for recognizing face images under partial occlusion.

Contents

Declaration	i
Dedication	ii
Acknowledgment	iii
Abbreviations	iv
Abstract	v
1 Chapter One	
Introduction	1
1.1 Background of the Study	1
1.2 Problem Statement	4
1.3 Objective of the Study	6
1.4 Significance of the Study	6
1.5 Research Methodology	7
1.6 Statistical Techniques for Evaluating the Performance of Al- gorithms	8
1.7 Data Acquisition	9
1.8 Research Design	10
1.9 Limitation of the Study	11

1.10	Structure of Thesis	11
2	Chapter Two	
	Review of Literature	12
2.1	Introduction	12
2.2	Definitions and Overview Face Recognition	12
2.3	Historical Prospective of Face Recognition	13
2.4	Problems with face recognition system	16
2.4.1	Face Detection Errors: False Acceptance Rate & False Recognition Rate	17
2.5	Definition of Principal Component Analysis (PCA)	17
2.6	Definition of Independent Component Analysis (ICA)	18
2.6.1	Mathematical Background	20
2.7	Some Measures of Non-Gaussianity	22
2.8	Singular value Decomposition (SVD)	22
2.9	Summary	24
3	Chapter Three	
	Research Methodology	25
3.1	Introduction	25
3.2	Data Acquisition	25
3.3	Research Design	26
3.4	Preprocessing Stage	27
3.5	Resizing of the face image	28
3.6	Denoising of the face image	29
3.7	Mean Centering	29

3.8	Recognition Processes	30
3.9	Image Reconstruction Process Using DWT-PCA/SVD Algorithm	30
3.10	Application DWT-PCA/SVD Algorithm	31
3.11	Discrete Wavelet Transform	33
3.12	The Implementation of DWT-PCA/SVD Algorithm	36
3.13	Matrix & Function of Haar Transforms	38
3.14	Statistical Test Techniques	40
3.15	Testing for Univariate Normality	40
	3.15.1 Basic Descriptive Statistical Analysis	41
	3.15.2 Further Statistical Analysis	41
3.16	Parametric & Non-Parametric Statistical Analysis	42
3.17	Face Recognition Rate	42
3.18	Summary	43
4	Chapter Four	
	Presentation of Results & Discussion	44
4.1	Introduction	44
4.2	Results & Discussion	44
4.3	Numerical Analysis of DWT-PCA/SVD Algorithm	46
4.4	Statistical Analysis of DWT-PCA/SVD Algorithm	48
	4.4.1 Basic Descriptive Analysis	49
	4.4.2 Further Statistical Analysis	51

4.5	Summary	52
5	Chapter Five	
	Summary, Conclusion & Recommendation	54
5.1	Introduction	54
5.2	Summary	54
5.3	Conclusion & Recommendation	56

List of Tables

1.1	Areas of Applied Facial Recognition	7
4.1	Basic Descriptive Analysis	50
4.2	Further Statistical Analysis	51
4.3	Non-Parametric Test Statistic	52

List of Figures

1.1	<i>Sample of Subject in the MIT (2003-2005) database</i>	4
1.2	<i>Sample of Subject in JAFFE database</i>	4
1.3	<i>Sample of Subject in MIT & JAFFE database</i>	9
1.4	Research Design	10
3.1	Plate	26
3.2	Research Design	27
3.3	Reconstructed half-part (left and right) of the human face . . .	32
3.4	Discrete Wavelet Transform (DWT) Process	36
4.1	Reconstructed images from right and left half-image(MIT 2003- 2005 database)	45
4.2	Reconstructed images from right and left half-image (JAFFE)	46
4.3	R_{dj} difference	49

Chapter One

Introduction

1.1 Background of the Study

Machine learning has become one of the emerging research fields in the mathematical sciences. Face recognition is a very paramount research field spanning numerous research study areas and disciplines. This is because, face recognition has various applied applications which include bankcard identification, security monitoring, access control and surveillance control systems. All these applications are very vital for effective and efficient communication and interactions among people.

According to Galton (1889), the traditional way of classifying faces is by collecting facial profiles as curves and finding their norms, and also by classifying other profiles by their deviation from the norm. It was realized that, these classifications of facial profiles are multi-models.

Recent changes in face recognition systems have revealed that, these rapid changes in the development face recognition are as a result of active development of algorithm, accessibility of larger face recognition database and the

statistical and mathematical techniques used for evaluating the performance of the facial recognition algorithm.

Literature has revealed that, face recognition modules can be expressed as: static (still) or video images of scene, verify one or more persons. This is done by comparing with faces in the database. Verification of persons by means of comparing face recognition's can be grouped into several aspects which may differ. Firstly, an authorized user of a personal identification classification is considered cooperative, and identify claim. Secondly, an automatic authorization mechanism must run in real-time for user acceptance.

Finally, in the recognition experiment, only images of people from the training database will be displayed in the system, and the situation of the importer (most likely a person who was previously invisible) is usually the most important for identity verification. Face recognition: biometric method which involves automatic techniques for verification and identification of a living person based on his or her physiological features. In all, the biometric identification system uses the physiological features of a person and these include fingerprint, iris pattern or behavioral patterns such as hand writing, voice or key-stroke pattern to identify a person. Biometric face recognition devices are explained in three steps.

- Sensor and its observation: this type of sensor and the method of observation is subject to the type of biometric face recognition device used in the process. This gives the biometric signature structure of the individual.
- Algorithm is used on a biometric signature by “normalizing” this sig-

nature so that it is in the same format i.e. view, resolution, size etc. as the biometric signature on the system database.

- The matcher compares the normalized structure of a signature with the normalized signature set on the system database, and provides similar scores, and compares the personal normalized signature with each signature in the database.

In designing a facial recognition structure, we require an image as an input to our program. To recognize a face, the first step to verify in the image is to check whether it actually contains a face. If the image does not have a face, there is nothing recognizable, so using facial recognition software will be meaningless. Therefore, the best step is to verify the existence of at least one face in the entire input image. Facial recognition systems do not necessarily have to be able to detect faces in an image.

In the process of the face detection, the pattern recognition proceed by normalizing the face image that contribute to the geometry and changes by information of the location and appearance of face contours, identifying the face using good classification algorithms type and post processing the result using model-based structure.

The study will not strictly on face identification but rather, it will churn on 'Half Facial Recognition'. In the half face identification, the research will employ the following algorithms: Principal Component Analysis and Singular Value Decomposition (PCA/SVD) face algorithm and in addition, use the Discrete Wavelet Transform as preprocessing stage for recognition, identification and image matching.

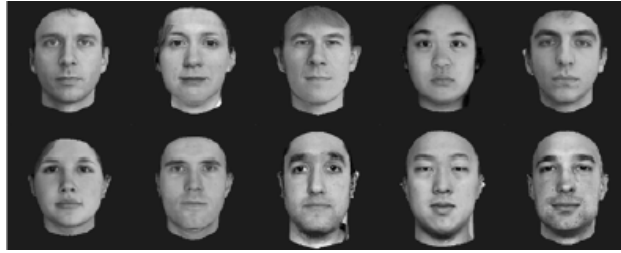


Plate 1.1: *Sample of Subject in the MIT (2003-2005) database*



Plate 1.2: *Sample of Subject in JAFFE database*

Over the years, almost everything has been computerized. However, technology is not always hundred percent foolproof. Errors still occur, and the machine is prone to discrepancies. Therefore, under the constraints of time and space, scientists and programmers are constantly developing new and improved algorithms to increase the success rate and make it as close to the maximum efficiency as possible.

1.2 Problem Statement

According to Turk and Pentland (1991b), face recognition algorithms' performances are restricted by constrained environments. Some of these constraints are illuminations, age charging, occlusion of face and face position. In the case of partially occluded faces, occlusion-insensitive, local matching and reconstruction techniques have been used for identification (Wei, 2014).

A special case of partially occluded faces where either the left or right face is occluded or segmented and the remaining half (non-occluded) face is used for recognition can be regarded as performing face recognition using half-face images (Jia and Martinez, 2009). Singh and Nandi (2012) applied PCA to the whole, left and right half faces and calculated the efficiency of their algorithm. Asiedu et al. (2020) tested FFT-PCA/SVD algorithm on reconstructed face database. They found that, the numerical evaluation results of the recognition rate on the performance of FFT-PCA/SVD algorithm in left reconstructed and right reconstructed face images were 95% and 90% respectively. Statistical evaluation of the algorithm performances, however, shows that the average recognition distance for the left and right reconstructed face images are different.

The performance of the DWT-PCA/SVD face recognition algorithm on varying head tilts/poses was evaluated by Asiedu et al. (2017). Their study revealed that, the recognition rate of the DWT-PCA/SVD algorithm declines for headposes greater than 20° . The algorithm gave a perfect recognition rate when used to recognize face images captured under angular constraints less than or equal 20° . They recommended the Discrete Wavelet Transform (DWT) as a viable noise reduction mechanism.

It can be inferred from the above literature and current advances that, the performances of face recognition algorithms are still hindered by occlusion on the face images. To this end, the study leveraged on the property of bilateral symmetry of frontal faces to reconstruct half face images (partial occluded faces) and assessed the performance of DWT-PCA/SVD face algorithm on the reconstructed face images database.

1.3 Objective of the Study

The objective of the study is to assess the performance of DWT-PCA/SVD algorithm on reconstructed face images. Specifically, the study seeks to:

- Estimate some numerical measures (Recognition Rate (RR), Error rate (ER) and run time) of the algorithm.
- Statistically assess the performance of the algorithm on the reconstructed database.

1.4 Significance of the Study

An efficient and resilient face recognition algorithm is paramount in the attempt to solving problems related to image processing and recognition, which are all real-life problems in machine learning and artificial intelligence. According to Marques and Graña (2012), face recognition is a dedicated process in the brain. Iris scan, speech recognition, fingerprints etc. are also other methods of identification which are also accurate in recognizing individuals.

Table 1.1: Areas of Applied Facial Recognition

Area	Areas of Applied Facial Recognition
Biometric	Personal Identification (NHIS cards, Driving License, Bankcard identities etc).
Security monitoring	Video surveillance
Access control	Secure access authentication
Leisure centers	Camera Photo and video games
Information security	Data privacy, user authentication and accessing security.

1.5 Research Methodology

Half facial recognition study aims at performing recognition algorithm on a created face in a database and analyzing the recognition performance of the algorithm. The facial image was passed through a face recognition module in the system for processing. It was then transformed into a workable, acceptable and compatible format (uniform dimension). The entire half facial recognition processes comprise of preprocessing, feature extraction noise reduction and recognition stage. The espoused preprocessing procedures were basically mean centering, application of the DWT-PCA/SVD and feature extraction. These aim at helping to reduce the noise level and give a better estimation of the parameters.

Unique half facial image feature was extracted and stored for recognition.

This normally occurs during the facial extraction stage. The facial features obtained from the extraction process or stage were passed to the classification stage for the image to be classified appropriately based on the available database used. In the Implementation of the half facial recognition, the study proposed a recognition design and also samples of image from the database were trained.

To ensure that the recognition is done accurately, a new half facial image was introduced into the system. The features of the image were determined by the algorithm. According to Asiedu et al. (2016), the weight of a test face and the known weight of the same image in the database can be compared by finding the norm of the difference between them. A maximum or a minimum difference signified poor and close match respectively.

1.6 Statistical Techniques for Evaluating the Performance of Algorithms

The research work seeks to evaluate the performance of the algorithms used for the study. The evaluation is done by the following basic statistics:

- Parametric Statistics (Paired Sample T-test)

Paired Sample T-test: This test is sometimes called the dependent t-test and is defined as the statistical technique which helps in determining if the mean difference between two kinds of observations is zero. In paired sample t-test, the groups are measured twice, and this results in pairs of observations. The above-mentioned statistical tests are used after their underlying assump-

tions are satisfied; if not, the study will use the non-parametric counter for data analysis.

1.7 Data Acquisition

The main objects of data collection are images captured under variable constraints and are stored at the Japanese Female Facial Expressions database (JAFFE) and Massachusetts Institute of Technology (MIT) database. The collected images are resized into uniform dimensions and captured into a face database.

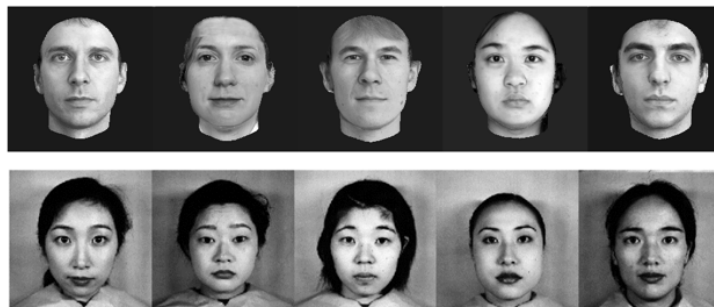


Plate 1.3: *Sample of Subject in MIT & JAFFE database*

1.8 Research Design

The first stage in the recognition process is to preprocess the train images using the adopted preprocessing mechanism (mean centering and discrete wavelet transform (DWT)). Test images, also known as the "unknown face", are exposed to the entire recognition process shown below and kept's vital information in the database for comparison and identification purposes. The PCA process reduces the high dimension face image introduced, to small dimension thereby keeping important information for recognition. The database shown in Figure 1.4 contains the half train image set which is trained per the recognition module and its corresponding information stored in database for recognition.

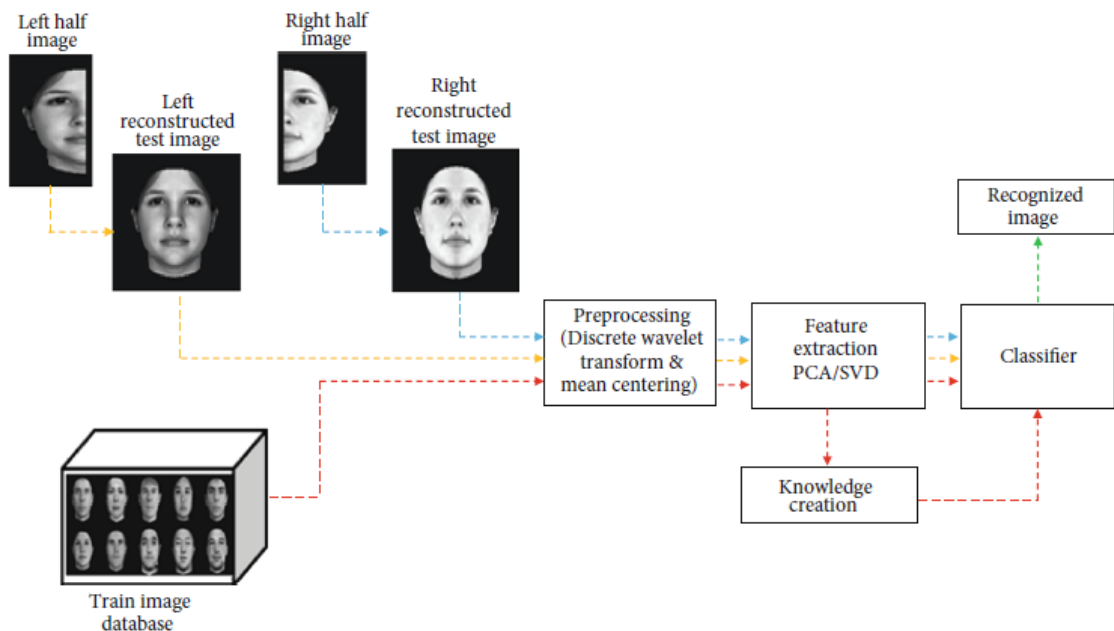


Figure 1.4: Research Design

1.9 Limitation of the Study

The study is limited to only Massachusetts Institute of Technology (MIT) database and Japanese Female Facial Expression (JAFFE) database.

1.10 Structure of Thesis

The research work is organized into five main chapters. The first chapter considers the background of the study, objectives of the study, research objectives, significance of the study and organization of the thesis. Chapter two contains the theoretical framework which covers literature reviews on the subject area, authoritative and other relevant theories propounded which form the basis for the study. Chapter three includes information on the methodology of the study. It also covers the algorithms used in the research work and also the Mathematics laboratory software used in running the algorithms on the images for analysis and discussion. Chapter four covers data analysis and discussion of the result obtained. Chapter five has the summary of the findings obtained, conclusions made based on the results, recommendations, and direction of future research to be taken.

Chapter Two

Review of Literature

2.1 Introduction

This chapter looks at definitions and gives an overview of Facial Recognition on Half image completion on some algorithms used in the recognition processes, face recognition systems, preprocessing (Eigen features), Hidden Markov model, face detection and feature extraction (Geometrical feature matching), classification and noise detection in image processing, linear discriminant and principal component analysis.

2.2 Definitions and Overview Face Recognition

Facial recognition is a technology that can recognize or identify individuals from video sources through digital images or video frames. There are several processes in which requires the operation of facial recognition systems by matching selected facial features from a given image with faces in a database. It is also known as a Biometric Artificial Intelligence based application that

can uniquely identify a person by analyzing patterns based on the individual's facial patterns, contours and structure (Petrescu, 2019).

In addition, commercial identification proof and promoting device has become famous in recent times, this is as a results of applications such as advanced human-computer video surveillance, automatic indexing of images, and video database, among others (Bramer, 2006).

2.3 Historical Prospective of Face Recognition

During 1964 and 1965, Bledsoe with Helen Chan and Charles Bisson, worked on using the computer to recognize human faces. In 1964 and 1965, Bledsoe, alongside Helen Chan and Charles Bisson, dealt with utilizing the principal component to recognize human faces. (Bledsoe, 1966; Bledsoe and Chan, 1965). They were pleased with this work, but since the findings were given by an anonymous knowledge office that did not permit a lot of exposure, little of the work were distributed (Bergstra and Klop, 1984). "In view of the accessible references, it was uncovered that the Bledsoe's underlying methodology included the manual checking of different tourist spots on the face, for example, the eye environment, mouth, and so on. These were numerically pivoted by computer to compensate for pose variation" (de Leeuw and Bergstra, 2007). The length between landmarks spots were computed, registered and contrasted between image (de Leeuw and Bergstra, 2007). Given an enormous information base on pictures (in effect, a book of mug shots) and a photo, the issue was to choose from the database a little arrangement of records with the end goal that, one of the images' records coordinated

the photo. The achievement of the strategy could be estimated as far as the proportion of the appropriate response rundown to the quantity of records in the database. Bledsoe (1966) described the following difficulties:

These recognition algorithms are challenged by varying landmarks such as head turn and tilt, lighting power and point, outward appearance, maturing, and so on. Some different endeavors at face recognition by machine have taken into account practically no changeability in these amounts. However, the strategy for correlation (pattern matching) of natural optical data, which is regularly utilized by certain specialists, is sure to come up short in situations where the fluctuation is extraordinary.

This undertaking was marked man-machine in light of the fact that humans extracted the directions of a lot of highlights from the photos, which were then utilized by the computer for recognition. Utilizing a designs tablet, the operator would extricate the coordinates of features such as, the focal point of understudies, within corner of eyes, the external corner of eyes, purpose of windows top, etc. These operators could measure about 40 pictures in 60 minutes. In the recognition stage, the arrangement of distances was contrasted and the relating distances for each photo, yielded a distance between the photo and the information database.

Since it is impossible that any two pictures would coordinate in head pivot rotation, lean, tilt, and scale (way from the camera machine), each distance of separations is standardized to speak to the face in a frontal direction. To achieve this standardization, the program first attempts to tilt the lean, and its revolution.

Eigenface, also called Karhunen-Loève, is an expansion of the most thor-

oughly investigated approaches to face recognition. The expansion comprises of eigen image, eigenvector and principal component (Kirby and Sirovich, 1990). This principal component is efficiently used to analyse and represent images of faces. Their argument was that any face images could be approximately reconstructed by a small collection of weights for each face and a standard face image. Description of the weights of each face are obtained by projecting the face image onto the eigen image (Turk and Pentland, 1991a). Eigen faces that were used were motivated by the methods of Kirby and Sirovich, for face detection and identification.

In numerical terms, eigenfaces are the essential segments of the distribution of faces, or the eigenvectors of the covariance metrics of the eigenvectors of face images. The eigenvectors are orchestrated by requesting to show various measures of the variation, individually and how they appear. Each face can be introduced precisely by linear combination of the eigenfaces. It can likewise be approximated by utilizing just the "best" eigenvectors with the biggest eigenvalues. The best M eigenfaces develop an M dimensional space, i.e., the "face space".

As the image incorporates a huge amount of background region, the above outcomes are affected by the background. The authors clarified the powerful execution of the system under various lighting conditions by noteworthy relationship between images with changes in illumination. Notwithstanding, Grudin et al. (1997) demonstrated that the relationship between images of the entire face is not productive for acceptable recognition execution. Illumination normalization by Kirby and Sirovich (1990) is normally important for the eigenfaces approach. Zhao and Yang (1999) projected another technique

to process the covariance matrix utilizing three images which were taken in different lighting conditions to represent self-assertive illumination impacts, if the object is Lambertian. Pentland et al. (1996) protracted their initial work on eigenface to eigen features matching to confront segments, for example, eyes, nose, and mouth. They utilized a measured eigen space which was made up of the above eigenfeatures (i.e., eigeneyes, eigennose, and eigenmouth). This technique would be less fragile to appearance changes than the standard eigenface techniques . The system accomplished a recognition rate of 95 percent on the FERET information of 3,000 people using 7,562 pictures captured from them of different pose. In conclusion, eigenface shows up as a quick, straightforward, and practical method. However, in all, it does not offer invariance over varieties in scale and lighting conditions. According to Chang et al. (2003) experiments with ear and face recognition, utilizing the standard principal component analysis approach, indicated that the recognition execution is basically indistinguishable, utilizing ear image or face image and joining the two for multimodal recognition which brings about a statistically significant performance improvement.

2.4 Problems with face recognition system

Face recognition systems were intended to work in controlled situations: access control frameworks and electronic identification. Face recognition is an extremely troublesome issue. As a result, it forms part of the most comparative design of face joined with various varieties of images of a similar face. The major problems of image processing are illumination, ageing, distance

changing, occlusion and similar faces. The image of a face changes with outward appearance, age, perspective, distance, light, clamor, barriers and so forth.

2.4.1 Face Detection Errors: False Acceptance Rate & False Recognition Rate

The false acceptance rate is the probability that the biometric security system will mistakenly accept an access attempt by an unapproved person. A system's FAR normally is expressed as the proportion of number of false acceptances divided by number of identification attempts. The false recognition rate (FRR), is the measure of the probability that the biometric security system will mistakenly reject an access attempt by an approved person. According to Gottumukkal and Asari (2004), "False recognition rate normally is stated as the proportion of the number of false recognitions divided by the number of identification attempt".

2.5 Definition of Principal Component Analysis (PCA)

The main recognition algorithm used today is the Principal Component Analysis (PCA). Consistently, there have been numerous enhancements and extensions to the first PCA. Studies have demonstrated that the outcome of the recognition algorithm can be incredibly improved by applying preprocessing methods to the image before putting it into the algorithm. Accordingly,

notwithstanding, the Multi-direct PCA, will utilize Empirical Mode Decomposition (EMD) for preprocessing. Besides, it can be run as an Expectation Maximization (EM) algorithm which gives the maximum Likelihood estimates values information which might be absent in the database.

The Independent component analysis (ICA) method first presented by Vittoz and Arreguit (1989) might be considered as an augmentation to PCA Nordhausen and Oja (2018), then again, actually PCA centers around identifying components on second-order statistics, ICA additionally consider higher-order properties which permits it to look for segment that are mutually independent. The least complex type of ICA happens when an m -dimensional vector, $X = (x_1, x_2, \dots, x_m)$ of length l is derived through the mixing of an m -dimensional “source” vector $S = (s_1, s_2, \dots, s_m)$, also of length l , commonly referred to as the independent component.

The ICA are aims to be non-Gaussian, which are statistically independents and with zero mean. The ICA are placed into vector-form, and also assumed that the mixing is both direct and fixed.

2.6 Definition of Independent Component Analysis (ICA)

As mentioned previously, the objective of ICA is to find projections which yields components that are as independent as possible, where independence means that the joint probability density function can be factorized as

$$f(y_1, y_2, \dots, y_m) = f_1(y_1) \cdot f_2(y_2) \dots f_n(y_n),$$

where, f_i , represents the marginal probability density function of y_i and $f(y_1, y_2, \dots, y_m)$ represents the joint probability density function. It has further more been illustrated that, as inferred from the central limit theorem, this objective is equivalent to finding the directions of maximum non-Gaussianity.

ICA consists of three basic elements which includes:

1. Identifying some measures of the non-Gaussianity of projection $W'Z$, often referred to as contract function.
2. Discovering some algorithm that will maximize this non-Gaussianity.
3. One of the most utilized measure of non-Gaussianity is kurtosis, but this measure has been discovered to be very sensitive to outliers and negentropy which is used to calculate the level of quantity.

Therefore, PCA attempts to identify uncorrelated or related components and ICA also attempts to sort out independent components. PCA, based on the linear correlation between pairs of data points, offers a way to extract structures that recur many times throughout a time series. One basic assumption of the PCA is that, variables are to be linearly independent (uncorrelated variables). This is due to higher order correlation which will not be considered. The fundamental objective of these algorithms is to remove independent components by:

- optimizing non-Gaussianity process,
- reducing the mutual information,
- using Maximum Likelihood (ML) estimation approached.

2.6.1 Mathematical Background

Independent Component Analysis (ICA) depends on the presumption that source signals, due to various physical processes which are statistically independent in a way that the real values of one signal gives no information about the estimation of the others. Numerically, two factors α and β are factually independent if their joint likelihood probability density function (pdf) is the result of their individual pdfs

$$p(\alpha, \beta) = p(\alpha)p(\beta).$$

Taken expectation of their joint pdf

$$E[\alpha^{n_1}\beta^{n_2}] = \int \int p(\alpha, \beta)\alpha^{n_1}\beta^{n_2} dx dy = E[\alpha^{n_1}]E[\beta^{n_2}].$$

If the α & β are correlated, but are merely uncorrelated, then it is valid only when $n_1 = n_2 = 1$, that is $E[\alpha\beta] = E[\alpha]E[\beta]$. Normal distribution or the Gaussian process is ordinarily determined by the two moment, (mean ($\bar{\alpha}$), standard deviation (s)). For non-Gaussian variables, all moments may be needed to specify the distribution and higher order correlation dimension must be taken into consideration to accomplish linear independence. Let $\lambda(\alpha, t) = [\mu_1, \mu_2, \dots, \mu_n]^T$ be the observation data, which can be described by the relation $\lambda = A\rho$, where ρ is a matrix containing the unknown source signals and A is an unknown mixing matrix that mixes the sources to give the observation. Each signal varies over time and a signal is represented as follows $\rho_i = (\rho_{i1}, \rho_{i2}, \dots, \rho_{iN})$, where N is the number of time steps and represents

the amplitude of the signal ρ_i at the j^{th} time. Given two independent source signals $\rho_1 = (\rho_{11}, \rho_{12}, \dots, \rho_{1N})$ and $\rho_2 = (\rho_{21}, \rho_{22}, \dots, \rho_{2N})$, both signals can be represented as follows:

$$\rho = \begin{pmatrix} \rho_1 \\ \rho_2 \end{pmatrix} = \begin{pmatrix} (\rho_{11}, \rho_{12}, \dots, \rho_{1N}) \\ (\rho_{21}, \rho_{22}, \dots, \rho_{2N}) \end{pmatrix}$$

where $S \in R^{(p \times N)}$ is the space defined by the signals and ρ denotes the number of source signals. The source signals (ρ_1, ρ_2) can be mixed as follows; $\alpha_1 = a_1\rho_1 + a_2\rho_2$, where a_1 and a_2 are the mixing coefficients of α_1 , is the first mixture signal. The mixture signals α_1 are the weighted of the two signals (ρ_1, ρ_2) .

Moreso, the other signal (α_2) can be measured by changing the distance between the signals and the sensing device. It is computed as follows: $\alpha_2 = a_3\rho_1 + a_4\rho_2$, where a_3 and a_4 are the mixing coefficients of α_2 , is the second mixture signal.

Two mixtures are given as

$$\rho = \begin{pmatrix} \alpha_1 \\ \alpha_2 \end{pmatrix} = \begin{pmatrix} a_1\rho_1 + a_2\rho_2 \\ a_3\rho_1 + a_4\rho_2 \end{pmatrix} = \begin{pmatrix} a_1 & a_2 \\ a_3 & a_4 \end{pmatrix} \begin{pmatrix} \rho_1 \\ \rho_2 \end{pmatrix} = A\rho$$

where $\alpha \in R^{(n \times N)}$, denoted as the space which is the signals and n is the number of mixture signals. Also, the mixing coefficient (a_1, a_2, a_3, a_4) are used for transforming linearity source signals in α space as, $\rho \longrightarrow \alpha : \alpha = A\rho$ where, $A \in R$ is the mixing matrix of coefficients and defined as $\begin{pmatrix} a_1 & a_2 \\ a_3 & a_4 \end{pmatrix}$.

To increase some understanding into the inversion process, we consider first the "projection pursuit" approach (Kruskal, 1969) in which an unmixing vector is discovered, and that removes the most non-Gaussian conceivable (maximally – non-Gaussian) signal. This signal is then taken out from the arrangement of blended signs and the cycle is repeated. An approach to execute this methodology is to consider the kurtosis (k) of the signal ($\beta = w^T u$) as a proportion of non-Gaussianity.

$$Kurt(\alpha) = E\{\alpha\} - 3(E\{\alpha^2\})^2.$$

2.7 Some Measures of Non-Gaussianity

An important principle in ICA estimation of its parameters is Non-Gaussianity: In order to use non-gaussianity in ICA estimation, there is the need to have a mathematical measure of non-gaussianity of a signal. Also, before using any measure of non-gaussianity in ICA estimation, the signals should be standardized (eg. mean centered). Kurtosis, skewness and negentropy are some few mentioned commonly used measures of non- gaussianity.

2.8 Singular value Decomposition (SVD)

Singular value decomposition is measured from three different angles which are compatible with one other. Firstly, it can be seen as a method for transforming variables which are correlated to uncorrelated variables so as to reveal all the relationships in the main data point. Secondly, SVD is a technique

for locating and ordering the dimensions and observations through which these dimensions show greater variability. The final way of considering SVD is that, once the maximum variability is determined, it is possible to determine the best estimation of primary data items with fewer dimension (Baker, 2005). According to Hong (1991), the features of an image can be divided into four categories; namely, the transform coefficient, statistical pixel, visual and algebraic characteristics. Algebraic features or characteristics consisting of the inherent features of a face, have an excellent stability. According to Hong, the algebraic characteristics of the image is a genius feature in object recognition such as facial recognition, and so, an SVD-based recognition method is proposed. Hong (1991) tested the efficiency and effectiveness of singular value decomposition.

Asiedu et al. (2020), computed the average recognition for FFT-PCA/SVD algorithm and found out that, there were 95% and 90% average recognition error rate as 5% and 10% when left and right reconstructed face images are used as test image respectively. In Hong (1991), the error rate was recorded as 42.47% which is due to the statistical limitation of small sample. Cheng et al. (1992) also suggested a facial recognition techniques formed on the statistical model of small sample. This method uses singular values as features of a face. Hong constructed an optimal discriminate transformation to transform the main space of the singular vale (SV) vector into a new space with much smaller size than the original space, thereby reducing the results due to small samples.

2.9 Summary

Face recognition is a functioning examination field because of its likely use in assortment of law and commercial applications including controls, security observing and video surveillance. A biometric identification system dependent on physiological feature, facial recognition system is a distant, non-nosy system for checking personal(s) facial features in an easy-to- understand route without intruding on client movement. Chapter two (Literature review) reviews most of the effect in face recognition techniques focusing on all types of variations in facial image. Steps related to various challenges of facial recognition are discussed. Visual face recognition system have shown elite under obliged conditions, for example, frontal mug shot images and steady lighting conditions. Execution of visual face recognition debase under uncontrolled illumination condition as in outside surveillance applications. Face recognition experiences some challenges in recognizing disguised faces can be critical in very good quality security applications. Each facial recognition algorithm has its own advantages and disadvantages. Face recognition performance can be improved by the combination of information on different techniques. Assessment of the recognition rate and recognition error of algorithm performance on images were recommended as very important in computation evaluation in images processing (Asiedu et al., 2020; Hong, 1991).

Chapter Three

Research Methodology

3.1 Introduction

This chapter is dedicated to the methodology that was used in this study. It focuses on a detailed and comprehensive understanding of DWT-PCA/SVD. The following areas were deemed important for discussion: the source of data, methodologies used in the image processing, steps used in analyzing the image data, theories and concepts used in order to satisfy the study objectives. The research used three (3) stages in the data analysis of facial recognition procedure comprising: DWT as a noise filtering in the pre-processing stage, PCA/SVD as feature extraction (dimension reduction) and recognition.

3.2 Data Acquisition

The study employed a secondary database, which was extracted from Massachusetts Institute of Technology (MIT) and Japanese Female Facial Expression (JAFFE) database. The images were used for the study because they

are from standard database for benchmarking the recognition algorithms.

Plate 3.1. Shows the images of individuals face in MIT(203-2005) and JAFFE database.

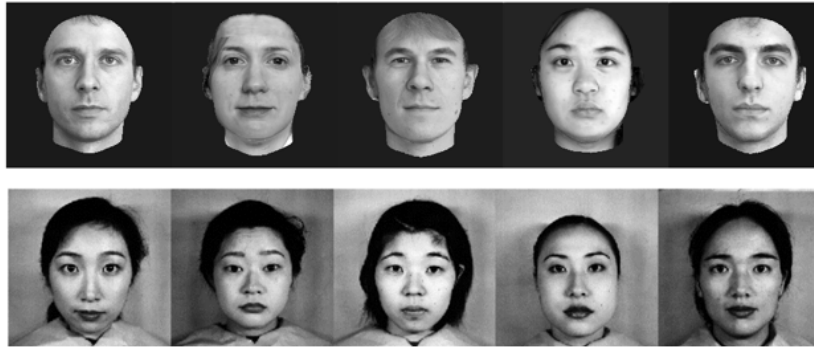


Plate 3.1: *Sample of Subject in MIT & JAFFE database*

3.3 Research Design

The first stage in the recognition process is to preprocess the train images using the adopted preprocessing mechanisms (mean centering and discrete wavelet Transform (DFT)). After preprocessing, unique face features are extracted using the PCA/SVD algorithm and stored in the system's memory as a created knowledge for recognition.

The performance of the study algorithm (DWT-PCA/SVD) was assessed on two test image databases: left reconstructed face images (test image database 1) and right reconstructed face images (test image database 2). The test images are also preprocessed using the mean centering and discrete wavelet transform (DWT) mechanisms.

Their unique features are also extracted using PCA/SVD for recognition.

These features are then passed to the classifier where they are matched with the train image features stored in the memory. It is important to note that only one test image database (left reconstructed face images or right reconstructed face images) is used in the face recognition module along with the train image database at a time. Figure 3.2 shows a design of the study recognition module.

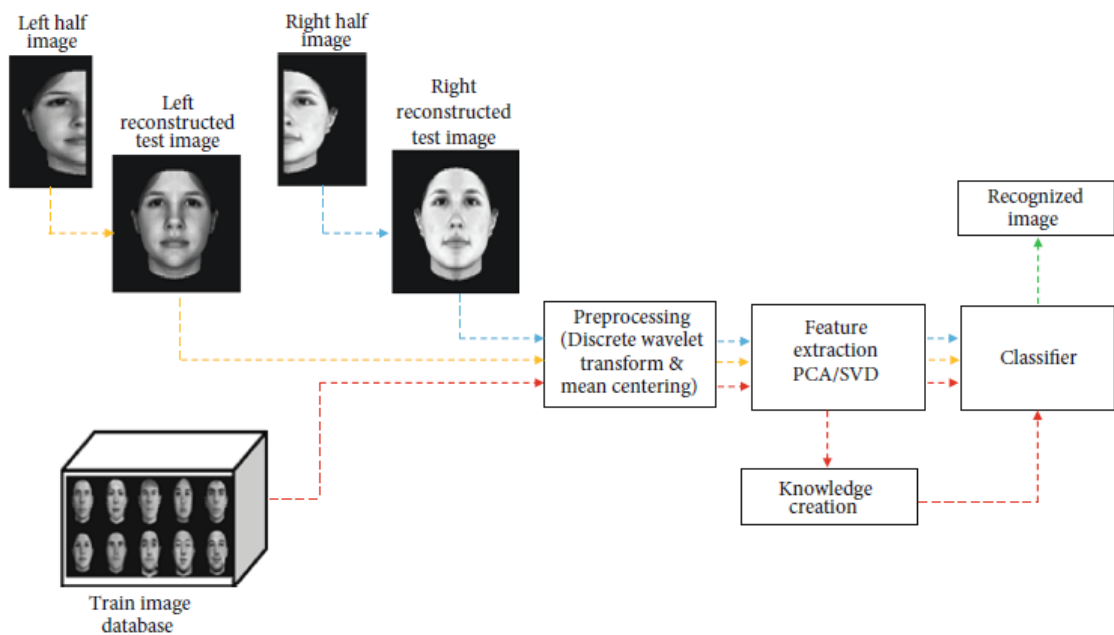


Figure 3.2: Research Design

3.4 Preprocessing Stage

Face image preprocessing helps to improve the quality of the facial image in order to achieve good recognition performance of the algorithm. The preprocessing phase is a useful stage in facial image representation and it is used as a noise reduction mechanism, proposed by Asiedu et al. (2016, 2020). The

pre-processing stage is an effective method to suppress unnecessary image feature distortion for further processing. This helps to drastically reduced the level of noise contained in an image data set and also makes the estimation process simpler and better adjusted to improve the recognition rate. In this study, we adopted the mean centering and discrete wavelet transform (DWT) as the preprocesssing mechanism. Face recognition involved the use of mean centering and Discrete Wavelet Transform (DWT) as denoising/filtering techniques in the preprocessing stage before facial features are extracted (Asiedu et al., 2016). According to Li et al. (2021), DWT can also be used in image encryption applications; although, a watermarking algorithm based on the DWT is not robust to geometric attacks. Please refer to Li et al. (2021) for more information on a robust double-encrypted watermarking algorithm for image encryption.

3.5 Resizing of the face image

The size of the image of face is of utmost important in facial recognition. Resizing an image of a face involves reshaping the image to a standard size which can be used. Every image of the face is imported from the database into Matlab program. The image of the face is resized into a uniform feature of 200×200 . Reddy et al. (2011) point out that resizing of facial image helps to reduce the lighting effect associated with visual images and therefore makes them best suited for PCA in image processing. The study used the process to reduce the mathematical complexity in the characteristics of face image extraction.

3.6 Denoising of the face image

Many researchers such as Yang et al. (2002) and Zhang et al. (2018) have revealed that naturally, facial images have the characteristics of a Gaussian noise due to the existence of lighting changes. For a face image in the dataset to be denoised (filtered), the study must use pixel-based filtering technique. In this research, mean centering and Discrete Wavelet Transform (DWT) are used to remove noise in the face image and retain important facial features for recognition.

3.7 Mean Centering

According to Asiedu et al. (2016, 2020), the mean centered face is deemed as the arithmetic mean of the training image vectors at each pixel point, having its dimensional size to be 200×200 . Let the image matrix $m_j = E(\mathbf{X}_j)$ be defined as

$$\bar{\mathbf{m}}_j = \frac{1}{N} \sum_{i=1}^N X_{ji}$$

where $(\mathbf{X}_j, j = 1, 2, \dots, n)$.

Hence, we have

$$\bar{\mathbf{m}}_j = \frac{1}{N} \sum_{i=1}^p \sum_{k=1}^p \mathbf{m}_{jik} \quad (j = 1, 2, 3, \dots, n), \quad (3.1)$$

where $N = (p \times p)$, distance = (rows of image \times columns of image) of the image data, \mathbf{X}_j . According to Asiedu et al. (2016), define $\bar{\mathbf{m}}_j$ as a constant vector of order $(p \times p)$ with all elements same as $(\mathbf{X}_j, j = 1, 2, \dots, n)$. The

centered mean is denoted by $W = (\mathbf{w}_1, \mathbf{w}_2, \mathbf{w}_3, \dots, \mathbf{w}_n)$, where

$$\mathbf{w}_j = \mathbf{X}_j - \mathbf{X}_j. \quad (3.2)$$

3.8 Recognition Processes

In this section, the research work attempts to address the problem of measuring and analyzing the reconstructed face by examining and evaluating the results of facial recognition algorithm that utilizes face symmetry. The research first seek to briefly explain the facial recognition algorithm used and the database used for the experiment.

3.9 Image Reconstruction Process Using DWT-PCA/SVD Algorithm

According to Asiedu et al. (2020), the left segmented half-images were reconstructed using the following steps;

- Rotate left segmented half-face image through 270° and denote it as F_{l1} .
- Rotate the left segmented half-face image through 180° and denote it as F_{l2} .

- Concatenate F_{l1} and F_{l2} as

$$T_l = [F_{l1}|F_{l2}].$$

Similarly, Asiedu et al. (2020), the right segmented half-images were reconstructed using the following steps;

- Rotate right segmented half-face image through 270° and denote it as F_{r1} .
- Rotate the right segmented half-face image through 180° and denote it as F_{r2} .
- Concatenate F_{r1} and F_{r2} as

$$T_r = [F_{r1}|F_{r2}].$$

The reconstructed image is then used in place of the full face image for face recognition.

3.10 Application DWT-PCA/SVD Algorithm

The images used in this work were collected from the database of the Massachusetts Institute of Technology (MIT) (2003-2005) and Japanese Female Facial Expressions (JAFFE). The research work used image data captured

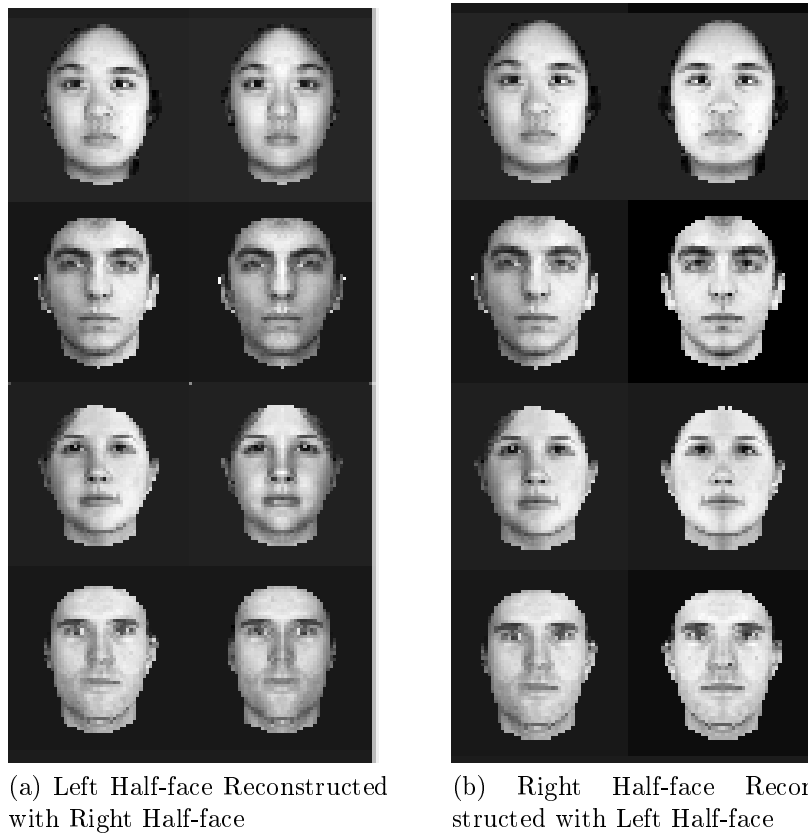


Plate 3.3: Reconstructed half-part (left and right) of the human face

under 0° pose from the MIT database and neutral face expressions from JAFFE. Different human face, making a total of 10 each from MIT and JAFFE database were trained and their left and right half face used in the reconstruction of the other right and left half face respectively. The image data was normalized into 200×200 for effective and easy processing of the image. To train the image database, the DWT-PCA/SVD algorithm was used. During the training stage, an important facial feature of the training data is extracted and stored in the database.

3.11 Discrete Wavelet Transform

Wavelet is a small wave. It is a very unique type of function, that shows oscillatory pattern for a short time and dies off (Karimi et al., 2012).

Discrete Wavelet Transform (DWT) is a technique that aids in transforming image pixels into wavelet for wavelet-based compression and coding. According to Kociołek et al. (2001), DWT is a linear transformation that operates on a data vector whose length is an integer power of two, transforming it into a numerically different vector of the same length. It provides a principal way of downsizing the range images and also captures both frequency and location information. According to Asiedu et al. (2016) DWT is centered on the domain in which the distribution of the frequency is transform in each process. Define L as low frequency band and H as high frequency band. LL sub-graph represents the lower resolution estimate of the original value, while mid-frequency and high frequency details subgraphs HL , LH and HH represent horizontal edge, vertical edge and diagonal edge details, respectively. Most of the energy is concentrated in low frequency sub-band of the four sub-bands, only the LL component (the approximate coefficients of the decomposition) is used to produce the next level of decomposition.

The LL sub-band contains only the low frequency components of the image and as such relatively free of noise. The sub-band HL represents major facial expression features. The sub-band LH (the vertical feature of outline) depicts face pose feature. The sub-band HH is the unstable band in all sub-bands because it is most often disturbed by noise, expression and pose. In view of these, the sub-band LL is the most stable sub-band (Lai and

Chang, 2006). The DWT refers to a set of transforms, each with a different set of wavelet basis functions. The Haar and Daubechies sets of wavelets are the two most common wavelets. Other forms of wavelet include the Morlet, Coiflets, Biorthogonal, and Mexican Hat Symlets.

The study adopt the Harr wavelet transform because it is the simplest wavelet transform and can efficiently support the interest of the study. The Harr wavelet applies a pair of low-pass and high-pass filters to image decomposition first in image columns and then in image rows independently. From transformation process described above, we rely on the proposed convolution theorem by Wei and Li (2019) which states that "a modified ordinary convolution in time is equivalent to simple multiplication operations for Offset Linear Canonical transform (OLCT) and Fourier transform".

According to Asiedu et al. (2017), if we consider a vectorized image \mathbf{X}_j of dimension N , where N is even, then the single-level Harr transform decomposes \mathbf{X}_j into two signals of length $N/2$. These are the mean coefficient vector U^1 with components

$$u_m = \left[\frac{\mathbf{X}_{j,2m-1}}{\sqrt{2}} + \frac{\mathbf{X}_{j,2m}}{\sqrt{2}} \right], m = 1, 2, \dots, \frac{N}{2} \quad (3.3)$$

and detail coefficient vector V^1 , with components

$$v_m = \left[\frac{\mathbf{X}_{j,2m-1}}{\sqrt{2}} - \frac{\mathbf{X}_{j,2m}}{\sqrt{2}} \right], m = 1, 2, \dots, \frac{N}{2}. \quad (3.4)$$

We concatenate U^1 and V^1 into another $N - vector$, which can be regarded as a linear matrix transformation of \mathbf{X}_j .

$$f^1 = [U^1|V^1]. \quad (3.5)$$

We then filter the transformed vector f^1 with the Gaussian filter. This is because the Gaussian noise is the default noise acquired due to illumination variation. The DWT is invertible so that the original signal can be completely recovered from its DWT representation (Bultheel et al., 1995) . The transform vector f^1 is inverted to X_j with components

$$\mathbf{X}_{j,2m-1} = \left[\frac{u_m}{\sqrt{2}} + \frac{v_m}{\sqrt{2}} \right], m = 1, 2, \dots, \frac{N}{2} \quad (3.6)$$

and

$$\mathbf{X}_{j,2m} = \left[\frac{u_m}{\sqrt{2}} - \frac{v_m}{\sqrt{2}} \right], m = 1, 2, \dots, \frac{N}{2}. \quad (3.7)$$

Figure 3.4 shows the DWT cycle using the Haar wavelet.

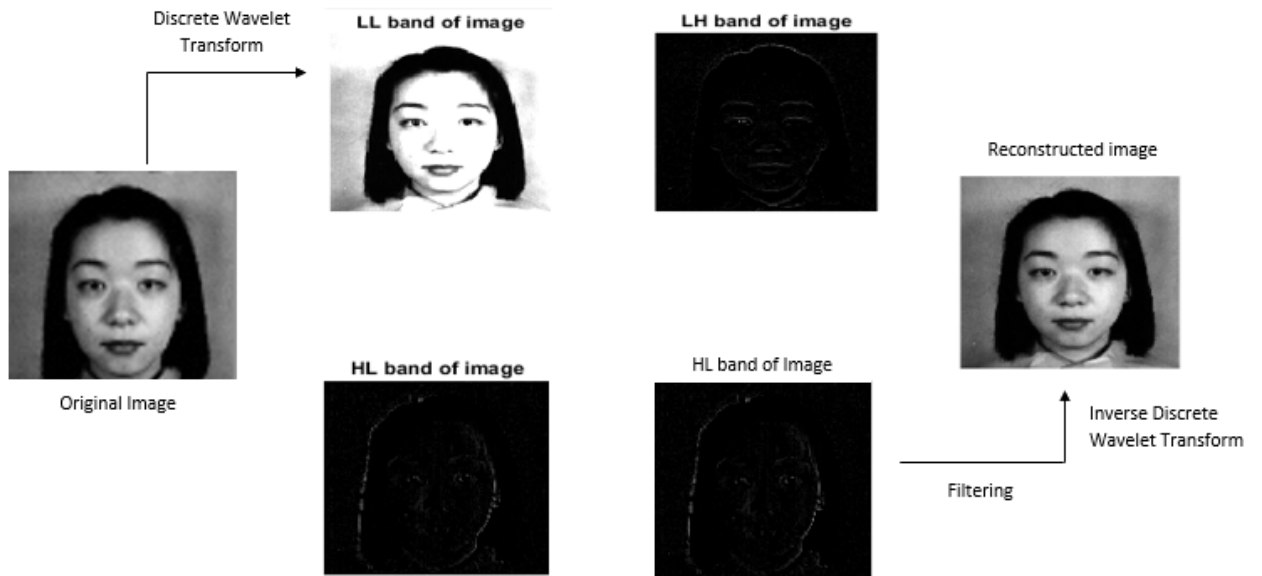


Figure 3.4: Discrete Wavelet Transform (DWT) Process

3.12 The Implementation of DWT-PCA/SVD Algorithm

The DWT-PCA/SVD algorithm was adopted as the recognition algorithm for this study. We motivate the mathematical foundation of the algorithm as follows. Define the sample X , whose elements are the vectorized form of the individual images in the study, as $X = (\mathbf{X}_1, \mathbf{X}_2, \dots, \mathbf{X}_n)$. Let

$$\bar{\mathbf{X}}_j = E(\mathbf{X}_j), \quad j = 1, 2, \dots, n \quad (3.8)$$

be the mean of the j th vectorized image; then, the mean centering of the j th image is given by

$$\mathbf{w}_j = \mathbf{X}_j - \bar{\mathbf{X}}_j. \quad (3.9)$$

The dispersion matrix \mathbf{C} of the vectorized image matrix is given as

$$\mathbf{C} = \frac{1}{n} \mathbf{W} \mathbf{W}^T, \quad (3.10)$$

where $\mathbf{W} = (\mathbf{w}_1, \mathbf{w}_2, \dots, \mathbf{w}_n)$ is the mean centered matrix. We now perform singular value decomposition (SVD) of the dispersion matrix \mathbf{C} , to obtain the eigenvalues and their corresponding eigenvectors. The SVD decomposition yields two orthogonal matrices \mathbf{U} and \mathbf{V} and a diagonal matrix Σ .

The eigenfaces are then computed as

$$e_j = \sum_{j=1}^n \mathbf{w}_j \mathbf{u}_j, \quad (3.11)$$

where \mathbf{u}_j is the j th column vector of the orthogonal matrix \mathbf{U} . The principal components extracted from the training set are given as

$$\beta_j = e_j^T (\mathbf{X}_j - \bar{\mathbf{X}}), \quad (3.12)$$

and $\beta_T = [\beta_1, \beta_2, \dots, \beta_n]$. These are stored in memory as created knowledge for recognition. We now consider test images from the two test image database (left reconstructed face images and right reconstructed face images). When an unknown face (test image) is passed through the recognition sys-

tem, its unique features are extracted as

$$\beta_j^* = e_j^T (\mathbf{X}_j^* - \bar{\mathbf{X}}), \quad (3.13)$$

where $\beta_T^* = [\beta_1^*, \beta_2^*, \dots, \beta_n^*]$ is the principal component (extracted features) of the test image. The recognition distances (\mathbf{d}) are computed as

$$\mathbf{d} = \|\beta - \beta^*\|. \quad (3.14)$$

The minimum Euclidean distance $d_{ji} = \min[\mathbf{d}]$, $j = 1, 2, \dots, n$, and $i = 1, 2$ is selected as the recognition distance for the closest match.

3.13 Matrix & Function of Haar Transforms

The group of N Haar function $h_t(x)$, ($t = 0, \dots, N - 1$) are defined on the interval $0 \leq x \leq 1$. The shape of the specific function $h_t(x)$ of a given index t depends on m and n ;

$$t = 2^m + n - 1. \quad (3.15)$$

For any value of $t \geq 0$, m and n are uniquely determined so that 2^m is the largest power of 2 contained in t ($2^m \leq t$) and $n - 1$ is the remainder; $n - 1 = t - 2^m$. Now the Haar function can be defined recursively as;

- when $t = 0$, the Haar function is defined as a constant

$$h_o(x) = \frac{1}{\sqrt{N}}. \quad (3.16)$$

- when $t > 0$, the Haar function is defined as

$$h_o(x) = \frac{1}{\sqrt{N}} \begin{cases} 2^{m/2}, & (n-1)/2^m \leq t < (n-0.5)/2^m \\ -2^{m/2}, & (n-0.5)/2^m \leq t < n/2^m \\ 0, & \text{Otherwise} \end{cases} \quad (3.17)$$

where p determines the amplitude and width of the non-zero part of the function and n determines the position of the non-zero part of the function. The N Haar function can be sampled as $t = s/N$, where $s = 0, \dots, N-1$ to form on an $N \times N$ matrix for discrete Haar transform. For example, when $N = 2$, we have

$$H_2 = \frac{1}{\sqrt{2}} \begin{bmatrix} 1 & 1 \\ 1 & -1 \end{bmatrix} \quad (3.18)$$

when $N = 4$, we have

$$H_4 = \frac{1}{2} \begin{bmatrix} 1 & 1 & 1 & 1 \\ 1 & 1 & -1 & -1 \\ \sqrt{2} & -\sqrt{2} & 0 & 0 \\ 0 & 0 & \sqrt{2} & -\sqrt{2} \end{bmatrix} \quad (3.19)$$

when $N = 8$, we have

$$H_4 = \frac{1}{\sqrt{8}} \begin{bmatrix} 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & -1 & -1 & -1 & -1 \\ \sqrt{2} & \sqrt{2} & -\sqrt{2} & -\sqrt{2} & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & \sqrt{2} & \sqrt{2} & -\sqrt{2} & -\sqrt{2} \\ 2 & -2 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 2 & -2 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 2 & -2 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 2 & -2 \end{bmatrix} \quad (3.20)$$

3.14 Statistical Test Techniques

The research on half face recognition algorithm will numerically and statistically be evaluated by some mathematical and statistical methods. These methods of evaluation will include recognition rate, average error rate, parametric and non-parametric methods. Now, in the case of statistical analysis, the method of analysis will depend on the underlying assumption been satisfied by the data. This will determine whether to use the parametric test statistics or the nonparametric test statistics.

3.15 Testing for Univariate Normality

Under the face recognition, the research seeks to check for univariate normality of the data. Univariate Normality test checks a given data set for similarity to the standard normal distribution. The null hypothesis states

that, the data set is similar to the standard normal distribution, therefore, a sufficiently small p-value indicates non-normal data. In order to test for normality, the following statistical analyses were used:

- Basic Descriptive Statistics (mean, skewness, kurtosis etc.)
- Further Statistics (Shapiro-Wilk test, Jargue-Bera test etc.)

3.15.1 Basic Descriptive Statistical Analysis

To ascertain the normality of the data, we perform some basic statistical analysis. This statistics will consist of the mean, median, skewness and kurtosis. Now, if mean value of the right and left reconstructed images distance is greater than the median value, then we say the left and right reconstructed images distance value is not normally distributed. Also, if the kurtosis value of right and left reconstructed images distance is less than 3, then it is an indication that the distribution of the recognition distance is not normal.

3.15.2 Further Statistical Analysis

Now to further justify the normality of the left and right reconstructed images distance value, there is a need to perform the Shapiro-Wilk test, Anderson-Darling test, Jargue-Bera test etc. A p-value of the test statistic which is less than the alpha-value (5%), is an indicates that the recognition image distance of the left and right reconstructed image is not normal and vise versa.

3.16 Parametric & Non-Parametric Statistical Analysis

Statistics analysis needs to be performed on the right and left reconstructed images distance but the statistical analysis is dependent on the normality of the right and left reconstructed images' distance data values. When the reconstructed recognition value is normally distributed, then the appropriate statistical test is the parametric test statistics. Similarly, when the reconstructed recognition value is not normally distributed, then the appropriate statistical test is the non-parametric counterpart (K-related sample measures eg. Wilcoxon signed-rank test).

3.17 Face Recognition Rate

To assess the performance of the algorithm, the research work seeks to compute the recognition rate of the algorithm. According to Asiedu et al. (2016, 2020), the recognition rate of face algorithm can be given as

$$R_{avg} = \frac{\sum_{i=1}^{t_{urn}} n_{cr}^i}{t_{run} \times n_{tot}} \times 100 \quad (3.21)$$

where,

t_{urn} is the number of experimental run,

n_{cr}^i is the number of correct recognitions in the i^{th} run, and

n_{tot} is th total number of face being tested in each run.

Also, the mean error rate of recognition is given as

$$ERR_{avg} = 100 - RR_{avg}. \quad (3.22)$$

Facial recognition algorithm places an important roll in the analysis of image recognition algorithm processes. The small the mean error rate, the better the recognition rate.

3.18 Summary

The chapter presented on the methods of image processing, recognition and evaluation on DWT-PCA/SVD algorithm. It also touched on image resizing and preprocessing (denoising and filtering) stage and also some discussion of other methods of image transformation were also reviewed. Steps in numerical and statistical evaluation of DWT-PCA/SVD algorithm performance were discussed in detail for essay implementation and reference.

Chapter Four

Presentation of Results & Discussion

4.1 Introduction

The chapter presents the image processing output results, as well as the numerical and statistical results. It focuses on a detailed and comprehensive explanation/demonstration of the normality of recognition distance by the use of histogram, quantile-quantile plot, correlation analysis, Shapiro-Wilk, Anderson-Darling test, Lilliefers test and Jargue-Bera test of normality. Further statistical analyses done in this chapter were the Paired t test and the K-Related Sample Statistics (Wilcoxon Signed-Rank Test).

4.2 Results & Discussion

From Figure 4.1 and 4.2 show the recognition distance (Euclidean Distance), recognition time, and recognition match. It can be observed from Figure 4.1 that, MIT (database 2003-2005) gave a full correct recognition match of the left reconstructed half images. However, there were two wrong matched

when the right reconstructed half images were utilized as test-runs images for recognition.

Original Image	Left Reconstructed Image	Recognition Distance	Recognition Time	Recognition Match
		314.87	0.84	Correct Match
		249.40	0.41	Correct Match
		183.03	0.67	Correct Match
		194.16	0.79	Correct Match
		319.30	0.85	Correct Match
		229.68	1.00	Correct Match
		115.59	1.00	Correct Match
		99.01	0.38	Correct Match
		217.88	0.39	Correct Match
		180.71	0.18	Correct Match

Original Image	Right Reconstructed Image	Recognition Distance	Recognition Time	Recognition Match
		245.64	0.91	Wrong Match
		138.11	0.47	Correct Match
		332.67	0.74	Wrong Match
		127.60	0.86	Correct Match
		253.20	0.89	Correct Match
		278.55	1.09	Correct Match
		230.03	1.03	Correct Match
		128.19	0.42	Correct Match
		179.84	0.27	Correct Match
		169.45	0.17	Correct Match

(a) Left Half-face Reconstructed with Right Half-face

(b) Right Half-face Reconstructed with Left Half-face

Figure 4.1: Reconstructed images from right and left half-image(MIT 2003-2005 database)

Similarly, it can be observed from Figure 4.2 that, using the JAFFE Half-face for recognition, there was one wrong match when the left reconstructed half images were used as test images for recognition. Also, it was observed that there were three wrong matches when the right reconstructed half images were used as test-runs images for recognition.

Original Image	Left Reconstructed Image	Recognition Distance	Recognition Time	Recognition Match
		650.54	2.71	Correct Match
		715.57	1.68	Correct Match
		715.77	2.11	Correct Match
		673.25	4.38	Correct Match
		1051.20	2.22	Wrong Match
		1136.80	2.70	Correct Match
		806.5	2.58	Correct Match
		444.72	1.22	Correct Match
		685.31	1.53	Correct Match
		657.87	0.65	Correct Match

(a) Left Half-face Reconstructed with Right Half-face

Original Image	Right Reconstructed Image	Recognition Distance	Recognition Time	Recognition Match
		515.66	2.68	Correct Match
		1022.60	1.86	Correct Match
		488.39	2.04	Correct Match
		909.99	4.56	Correct Match
		923.96	2.42	Wrong Match
		1240.40	3.07	Wrong Match
		841.73	2.68	Correct Match
		550.19	1.62	Correct Match
		1332.90	1.70	Wrong Match
		726.46	0.73	Correct Match

(b) Right Half-face Reconstructed with Left Half-face

Figure 4.2: Reconstructed images from right and left half-image (JAFPE)

4.3 Numerical Analysis of DWT-PCA/SVD

Algorithm

In order to assess the efficiency and effectiveness of the DWT-PCA/SVD algorithm, the research work seeks to evaluate the algorithm process by computing its average recognition and average error rate . According to Asiedu et al. (2016, 2020), the average recognition rate, R_{avg} , of an algorithm is defined by

$$R_{avg} = \frac{\sum_{i=1}^{t_{run}} n_{cr}^i}{t_{run} \times n_{tot}} \times 100,$$

where t_{run} is the number of experimental runs, n_{cr}^i is the number of correct recognition in the i^{th} run and n_{tot} is the total number of faces being tested

in each run. Also, in order to determine the weakness of DWT-PCA/SVD algorithm, the researcher computed the average error rate, E_{avg} as $100 - R_{avg}$. Using the left reconstructed face images, the total number of correct recognition $\sum_{i=1}^{10} n_{cr}^i$ for the research work algorithm is $(20 - 1) = 19$. The total number of experimental runs, $t_{run} = 10$ and the total number of images in a single experimental run, $n_{tot} = 2$.

The average recognition rate of DWT-PCA/SVD algorithm is

$$\begin{aligned} R_{avg} &= \frac{19}{(10) \times (2)} \times 100, \\ &= 95\%. \end{aligned}$$

Hence the average error rate is computed as,

$$\begin{aligned} E_{avg} &= 100 - R_{avg} \\ &= 100 - 95 \\ &= 5\%. \end{aligned}$$

Similarly, for the right reconstructed face images, the total number of correct recognition $\sum_{i=1}^{10} n_{cr}^i$ for the research work algorithm is $(20 - 5) = 15$. The number of runs, $t_{run} = 10$ and the number of images in a each run, $n_{tot} = 2$. The average recognition rate of research work algorithm DWT-ICA/PCA algorithm is

$$\begin{aligned} R_{avg} &= \frac{15}{(10) \times (2)} \times 100, \\ &= 75\%. \end{aligned}$$

Hence the average error rate is computed as,

$$\begin{aligned} E_{avg} &= 100 - R_{avg} \\ &= 100 - 75 \\ &= 25\%. \end{aligned}$$

From the above numerical results and assessment, DWT-PCA/SVD algorithm performs better when constructing the left half face than when the algorithm is constructing the right half face.

4.4 Statistical Analysis of DWT-PCA/SVD

Algorithm

Under statistical evaluation of DWT-PCA/SVD algorithm, the study attempts to evaluate the recognition distance generated from the running of the algorithm. Let the difference in recognition distance be R_{dj} and also let the recognition distance of the right and left reconstructed face images be r_{j2} and r_{j1} respectively. Mathematically

$$R_{dj} = r_{j2} - r_{j1},$$

where $j = 1, 2, 3, \dots, n$.

Now, the test of normality of R_{dj} , is to determine the next path of the analysis.

The following statistics and plots were performed to assess the normality of the data R_{dj} . Descriptive statistics (mean, median, variance, etc), Quantile-Quantile plot, correlation analysis, Shapiro-Wilk, Jargue-Bera test of normality and other test of normality were considered. A pictorial view of the R_{dj} image data gives some information of the nature of the distribution. Figure 4.3 below give the details

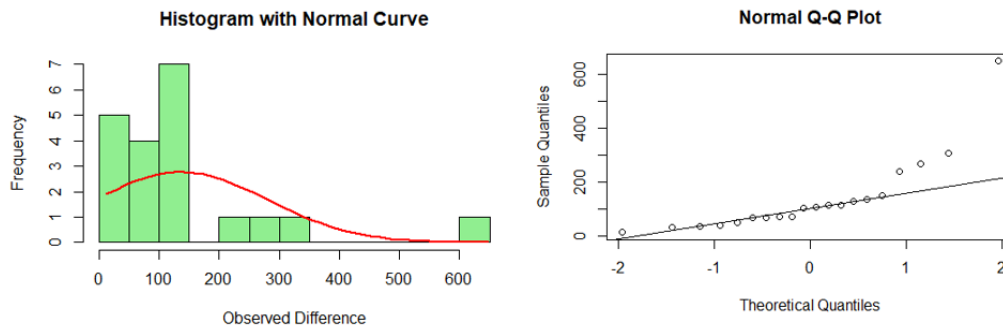


Figure 4.3: R_{dj} difference

From Figure 4.3 above, the histogram with normal curve shows that the R_{dj} values between right and left reconstructed images are not normally distributed. Similarly, the Quantile-Quantile plot shows a slight deviation of the point from the normal line. This gives the impression that the data points are not normally distributed.

4.4.1 Basic Descriptive Analysis

The fundamental tool used for data normality is to conduct a descriptive analysis on the data set which will be further checked by performing further statistical analysis to confirm or reject that the data is normally distributed. Table 4.1, below shows the descriptive statistics.

Table 4.1: Basic Descriptive Analysis

Statistics	Value	Statistics	Value
No. Observation	19	Variance (σ^2)	20769.89
Min. value	11.26	Standard deviation (σ)	143.23
Max. value	647.59	Skewness	2.42
Median	105.47	Kurtosis	8.99
Mean (\bar{x})	140.50	Correlation between r_{j2} & r_{j1}	0.869

From Table 4.1 above, the distribution of the data points shows that the recognition distance between left and right reconstructed images has an average recognition distance of 140.5 with a dispersion value of $\sigma^2 = 20769.89$ and $\sigma = 143.23$, representing the variance and the standard deviation of the data respectively. The Skewness value of 2.42 shows that, the recognition distance R_{dj} is long-right tail (positively skewed), meaning there are more high data point in the data set higher than the sample mean of the data. Also the kurtosis value of the data shows that the recognition distance R_{dj} is leptokurtic ($8.99 > 3$) which confirms that data has a long-right tail (positively skewed).

The paired sample Pearson correlation of the recognition distance (right and left) reconstructed half face is 0.889 and its probability value is 0.000. It shows that, a strong positive linear association exists between the two recognition distances or Euclidean distances. Also, the Pearson correlation coefficient p-value (0.000) signifies that the relationship is significant.

4.4.2 Further Statistical Analysis

Further statistical analysis was conducted to confirm the normality of the R_{dj} . Table 4.2 below gives us the statistics and their probability values (p-values).

Table 4.2: Further Statistical Analysis

Further Statistics	Test value	P-value	Decision
Shapiro-Wilk test	$W = .7204$	0.0001	Reject H_o
Anderson-Darling test	$A^2 = 1.6966$	0.0002	Reject H_o
Lilliefers test	$D = 1.1539$	0.0011	Reject H_o
Jargue-Bera test	$JB = 5.9915$	0.0001	Reject H_o

Hypothesis for Test of Normality

H_o : the R_{dj} image recognition distance is normally distributed

H_1 : the R_{dj} image recognition distance is not normally distributed

From Table 4.2 above, it can be observed that, all the further statistical test carried out to ascertain the normality of the recognition distance difference between the left and right reconstructed half face show that, the p-value is less than the alpha value. This leads to the rejection of the null hypothesis that the recognition distance difference (R_{dj}) is not normally distributed and this confirms the preliminary analysis conducted earlier.

Hence, the study resorts to using a non-parametric (K - related sample measure) method to analyze the data.

We denote distribution of r_{j1} and r_{j1} as F_1 and F_2 respectively.

Hypothesis Testing

$$H_0 : F_1 = F_2$$

$$H_1 : F_1 \neq F_2$$

Test Statistic

Table 4.3: **Non-Parametric Test Statistic**

RSHI-LSHI		P-value
Median	Wilcoxon signed rank test	
105.47	124	0.498

From Table 4.3 above, the median difference of the right and left reconstructed face images (RRI and LRI respectively) is 105.47. The test statistic value from the Wilcoxon signed rank test is 124 with its associated p-value, 0.498. Since the p-value of the Wilcoxon signed rank test (0.498) greater than the alpha value 0.05, the test fails to reject null hypothesis H_0 . Hence, we conclude that there is no significant difference between the median euclidean distance for the left and right reconstructed face images. This indicates that the reconstructed images have the same median recognition or euclidean distance at 5% level of significance.

4.5 Summary

This chapter gives detailed accounts of the study results and findings in the study area and these include: Face recognition process and image reconstruc-

tion process using DWT-PCA/SVD algorithm, mathematics and application of DWT-PCA/SVD algorithm and the result & discussion on numerical and statistical evaluation performance of DWT-PCA/SVD algorithm.

Chapter Five

Summary, Conclusion & Recommendation

5.1 Introduction

This chapter presents the summary of the research work, conclusion and recommendation of the study and also gives appropriate directions for future research works in image recognition process.

5.2 Summary

The study gives a vital assessment of the performance of DWT-PCA/SVD algorithm in the determination of half face image recognition. The research work made use of 20 images, out of which 10 were standard MIT image (2003-2005) database and 10 images from the JAFFE.

The study concentrated on noise reduction techniques during the image extraction stage and it includes the transformation process and Gaussian pro-

cess. It also adopted the use of DWT-PCA/SVD method for data extraction. The numerical evaluation of DWT-PCA/SVD algorithm shows that, the algorithm performs better when the left reconstructed half images are used as test images for recognition, then where right reconstructed half images are used. The average recognition rates and their associated error rates are 95%, 5% and 75%, 25% respectively. These result findings are in line with a work done by Asiedu et al. (2020) were they use the FFT-PCA/SVD algorithm on half face, Left and right reconstructed images.

The findings of the study are consistent with those of Asiedu et. al (2020) and Singh and Nandi (2021). The DWT-PCA/SVD algorithm is recommended as a suitable algorithm for the face image recognition under partial occlusion (half face images). The algorithm has a remarkable performance when used for recognition of the left reconstructed face images.

The average runtime of the modified DWT-PCA/SVD algorithm in half-face image recognition 2 seconds. The time used by the algorithm in the preprocessing phase contributed for the sharp speed of the algorithm.

A statistical test analysis of normality of the difference of the left and right reconstructed image distance showed that, the recognition or euclidean distance are not normally distributed. This was further revealed by the statistical test carried out in chapter 4.

In conclusion, the non-parametric method (Wilcoxon's Rank Test) was used to analyze the recognition distance of left and right reconstructed image and it showed clearly that, there is no statistically significant difference between the median recognition distance of the left and right reconstructed face image at 5% level of significance.

5.3 Conclusion & Recommendation

The study intensively used the PCA/SVD algorithm as data extraction techniques with Discrete Wavelet Transform and Gaussian process as noise reduction technique during the face image extraction process.

The use of the numerical evaluation on the DWT-PCA/SVD algorithm gave an appreciable performance on the left and right reconstructed half-images. The study further used the non-parametric method (Wilcoxon's Rank Sum Test) in assessing whether there is a significant difference in the left and right reconstructed images when the DWT-PCA/SVD algorithm is used. From the research findings, it is recommended that, the number of images used should be more in the study area.

The DWT-PCA/SVD is recommended as a good de-noising technique. Further research studies should consider the FFT-PCA/SVD algorithm. Asiedu et al. (2020), showed an improvement on the methods of noise reduction and half-face image reconstruction. The DWT-PCA/SVD is therefore recommended as one of the best noise variable algorithms for recognizing face images under partial occlusion.

Bibliography

- Asiedu, L., Adebajji, A., Oduro, F. T., and Mettle, F. O. (2016). Statistical assessment of pca/svd and fft-pca/svd on variable facial expressions.
- Asiedu, L., Mettle, F. O., and Mensah, J. A. (2020). Recognition of reconstructed frontal face images using fft-pca/svd algorithm. *Journal of Applied Mathematics*, 2020.
- Asiedu, L., Mettle, F. O., Nortey, E. N., and Yeboah, E. S. (2017). Recognition of face images under angular constraints using dwt-pca/svd algorithm.
- Baker, K. (2005). Singular value decomposition tutorial. *The Ohio State University*, 24.
- Bergstra, J. A. and Klop, J. W. (1984). Process algebra for synchronous communication. *Information and control*, 60(1-3):109–137.
- Bledsoe, W. W. (1966). The model method in facial recognition. *Panoramic Research Inc., Palo Alto, CA, Rep. PR1*, 15(47):2.
- Bledsoe, W. W. and Chan, H. (1965). A man-machine facial recognition system—some preliminary results. *Panoramic Research, Inc, Palo Alto, California., Technical Report PRI A*, 19:1965.

- Bramer, M. (2006). *Artificial Intelligence in Theory and Practice: IFIP 19th World Computer Congress, TC 12: IFIP AI 2006 Stream, August 21-24, 2006, Santiago, Chile*, volume 217. Springer Science & Business Media.
- Bultheel, A. et al. (1995). Learning to swim in a sea of wavelets. *Bulletin of the Belgian Mathematical society-simon stevin*, 2(1):1–45.
- Chang, K. I., Bowyer, K. W., and Flynn, P. J. (2003). Face recognition using 2d and 3d facial data. In *Workshop in Multidimonal User Authentication pp25-32*. Citeseer.
- Cheng, Y.-Q., Liu, K., Yang, J., Zhuang, Y.-M., and Gu, N.-C. (1992). Human face recognition method based on the statistical model of small sample size. In *Intelligent Robots and Computer Vision X: Algorithms and Techniques*, volume 1607, pages 85–95. International Society for Optics and Photonics.
- de Leeuw, K. and Bergstra, J. (2007). The scientific development of biometrics over the last 40 years. *The History of Information Security: A Comprehensive Handbook*, 10:263.
- Galton, F. (1889). Personal identification and description. *Journal of anthropological institute of Great Britain and Ireland*, pages 177–191.
- Gottumukkal, R. and Asari, V. K. (2004). An improved face recognition technique based on modular pca approach. *Pattern Recognition Letters*, 25(4):429–436.
- Grudin, M. A., Harvey, D. M., Timchenko, L. I., and Lisboa, P. G. (1997).

- Fast face recognition method using a multistage hierarchical network. In *1997 IEEE International Conference on Acoustics, Speech, and Signal Processing*, volume 4, pages 2545–2548. IEEE.
- Hong, Z.-Q. (1991). Algebraic feature extraction of image for recognition. *Pattern recognition*, 24(3):211–219.
- Jia, H. and Martinez, A. M. (2009). Support vector machines in face recognition with occlusions. In *2009 IEEE Conference on Computer Vision and Pattern Recognition*, pages 136–141. IEEE.
- Karimi, H. R., Pawlus, W., and Robbersmyr, K. G. (2012). Signal reconstruction, modeling and simulation of a vehicle full-scale crash test based on morlet wavelets. *Neurocomputing*, 93:88–99.
- Kirby, M. and Sirovich, L. (1990). Application of the karhunen-loeve procedure for the characterization of human faces. *IEEE Transactions on Pattern analysis and Machine intelligence*, 12(1):103–108.
- Kociołek, M., Materka, A., Strzelecki, M., and Szczypiński, P. (2001). Discrete wavelet transform-derived features for digital image texture analysis. In *international conference on signals and electronic systems*, pages 99–104.
- Lai, B.-L. and Chang, L.-W. (2006). Adaptive data hiding for images based on harr discrete wavelet transform. In *Pacific-Rim Symposium on Image and Video Technology*, pages 1085–1093. Springer.
- Li, Y.-M., Wei, D., and Zhang, L. (2021). Double-encrypted watermarking

- algorithm based on cosine transform and fractional fourier transform in invariant wavelet domain. *Information Sciences*, 551:205–227.
- Marques, I. and Graña, M. (2012). Face recognition with lattice independent component analysis and extreme learning machines. *Soft Computing*, 16(9):1525–1537.
- Nordhausen, K. and Oja, H. (2018). Independent component analysis: A statistical perspective. *Wiley Interdisciplinary Reviews: Computational Statistics*, 10(5):e1440.
- Pentland, A., Picard, R. W., and Sclaroff, S. (1996). Photobook: Content-based manipulation of image databases. *International journal of computer vision*, 18(3):233–254.
- Petrescu, R. V. (2019). Face recognition as a biometric application. *Journal of Mechatronics and Robotics*, 3:237–257.
- Reddy, K. R. L., Babu, G., and Kishore, L. (2011). Face recognition based on eigen features of multi scaled face components and artificial neural network. *International Journal of Security and Its Applications*, 5(3):23–44.
- Singh, A. K. and Nandi, G. C. (2012). Face recognition using facial symmetry. In *Proceedings of the Second International Conference on Computational Science, Engineering and Information Technology*, pages 550–554.
- Turk, M. and Pentland, A. (1991a). Eigenfaces for recognition. *Journal of cognitive neuroscience*, 3(1):71–86.

- Turk, M. A. and Pentland, A. P. (1991b). Recognition in face space. In *Intelligent Robots and Computer Vision IX: Algorithms and Techniques*, volume 1381, pages 43–54. International Society for Optics and Photonics.
- Vittoz, E. A. and Arreguit, X. (1989). Cmos integration of herault-jutten cells for separation of sources. In *Analog VLSI implementation of neural systems*, pages 57–83. Springer.
- Wei, D. and Li, Y.-M. (2019). Convolution and multichannel sampling for the offset linear canonical transform and their applications. *IEEE Transactions on Signal Processing*, 67(23):6009–6024.
- Wei, X. (2014). *Unconstrained Face Recognition with Occlusions*. PhD thesis, University of Warwick.
- Yang, M.-H., Kriegman, D. J., and Ahuja, N. (2002). Detecting faces in images: A survey. *IEEE Transactions on pattern analysis and machine intelligence*, 24(1):34–58.
- Zhang, L., Verma, B., Tjondronegoro, D., and Chandran, V. (2018). Facial expression analysis under partial occlusion: A survey. *ACM Computing Surveys (CSUR)*, 51(2):1–49.
- Zhao, L. and Yang, Y.-H. (1999). Theoretical analysis of illumination in pca-based vision systems. *Pattern recognition*, 32(4):547–564.