Chapter 1

Introduction

1.1 Introduction

This chapter introduces the research, wrinkles detection methods, and facial wrinkles as soft biometric. Also several important terms are defined. Moreover, it explains the problem statement, highlights the thesis contributions, and outlines the thesis structure.

1.2 Overview

There is a substantial number of researches on the facial image analysis over last few decades. Face recognition is one of these widely addressed applications due to its importance in several fields such as security Cohn et al. (2000). Some conditions such as poor resolution, occlusion, blur, illumination and pose variation may effects on the performance of facial recognition applications Batool et al. (2013). Latest research in face recognition Batool et al. (2013) have focused on new areas of using facial features rather than the typical features like: eyes, nose, mouth, chin, and ears. The new features are called facial micro-features, facial marks or facial soft biometric, it includes scars, freckles, moles, facial shape, skin color, hair color, facial hair, tattoos, eye color, shape of nose, beard, mustache and wrinkles Batool et al. (2013). The focusing in this thesis is on facial wrinkles.

Physiologically, many facial features are changes as people getting older, including facial wrinkle feature. It appears and become more obvious over years.

These wrinkles are changed based on the skin nature and muscle contraction Boissieux et al. (2000). Wrinkles can be defined as creases or small furrow in facial skin that caused by expressions or age. Ekman et al. Ekman & Friesen (1977) described wrinkles as a line with depth and sometimes the line have a width more than surface line. In some faces, the wrinkles may be temporary appear with certain actions, while other faces may show permanent wrinkle and it will be deepen with certain actions. In 2D images, the wrinkles are affecting the skin; it creates deep creases and sometimes creates curvature in the skin surrounding, this curvatures will affect the overall facial skin Ng et al. (2015*a*). The wrinkles characteristics can be described using two major factors: one of them used to define the location of wrinkles curve lines, this called furrow or macro, and the other one is bulge, which is used to give curved surface shape Wu et al. (1996).

Human eye can detect wrinkles easily, but it is such a difficult task to detect it automatically using image processing techniques, because the wrinkles shape is varying according to ethnic group, gender, age, and personal life style. Add to that, it depends on the image quality that affected by image acquisition environment Mawale & Chaugule (2016).

There are many different approaches in detecting the features changes on the face, including the detection of facial wrinkles. Earlier work in wrinkles detection was proposed by Loden et al. Lodén et al. (2007), they used silicone to produce the facial wrinkles by making replica using this silicone and made the measurements depends on it. But these old studies were not efficient enough, because it is very difficult to get silicone replicas same as the actual skin morphology. In 2014, Ng et al. Ng et al. (2015*b*) proposed Hybrid Hessian Filter (HHF) to detect and quantify the facial wrinkles automatically, their algorithm recorded very good results in detecting wrinkles.

The aim of this thesis is to automatic detect of facial wrinkles and investigate the uniqueness of these facial wrinkles in 2D images. In order to achieve our research aim and objectives, two methods were proposed: The *first* one is automatic wrinkles detection method which is the wrinkles detection phase, and the *second* proposed method that has been addressed is the possibility of using these facial wrinkles as soft biometric. Two datasets were used to test our proposed methods, state-of-the-art FERET and our new Sudanese dataset; a dataset that has been collected from Sudanese participants. Furthermore, this research presents comprehensive review for wrinkles detection algorithm including state-of-the-art methods, in addition to investigate the uniqueness of facial wrinkles .

This chapter is organised as follows. Section 1.2 describes an overview of this work. Section 1.3 is problem statement. Section 1.4 states the aim and objectives of this work; Section 1.5 lists the contributions made by the thesis. Finally, Section 1.6 provides an insight to the structure and presentation of the thesis.

1.3 Problem Statement

Existing wrinkles detection algorithms achieved good results Ng et al. (2015*a*) Ng et al. (2015*b*) with faces that contain medium and coarse type of wrinkles, but fine lines still caused a problem. Also algorithms are focusing on forehead horizontal line detection, while it is better to detect all wrinkles (horizontal + vertical). Furthermore, some researcher tried to study if facial wrinkles can be used as soft biometric Batool et al. (2013), but theresult was not conclusive because they were focused on forehead wrinkles. This study will develop a new automatic wrinkles detection algorithm for entire face, in addition to develop new algorithm to investigates and improve the discriminative power of facial wrinkles to identifying someone, also answer the question: is face wrinkles unique?

1.4 Research Aim and Objectives

The primary aim of this study is to develop new algorithms to improve the discriminative power of facial wrinkles to identifying someone and investigate the uniqueness of facial wrinkles. In order to achieve the primary aim, the following objectives have been established:

a. To conduct a comprehensive literature review on the use of wrinkles as soft biometrics and automated wrinkle detection techniques.

b. To develop new algorithm for automated wrinkles detection.

c. To investigate the uniqueness of facial wrinkles.

d. To test and compare the algorithms output with new type of dataset (Sudanese dataset)

e. To evaluate the performance of proposed algorithms on multiple datasets.

1.5 Contributions

The fundamental contributions of this thesis are:

a. New algorithm for automatic wrinkles detection is proposed.

b. New algorithm to investigate the uniqueness of facial wrinkles is proposed.

c. Modified Hybrid Hessian Filter is proposed as an extension to original HHF.

d. New Sudanese dataset of different ages have been collected and used it evaluate the proposed algorithms.

1.6 Thesis Organisation

This thesis is organised in two parts. The first part includes introductory chapters providing fundamental and background knowledge of the subject area, state of the art for wrinkle detection and soft biometric. The second part of this thesis includes two contributory chapters where proposed enhancement wrinkles detection method and proposed method to investigate the discriminative power of facial wrinkles as soft biometric are discussed. Finally, this thesis concludes the works and an insight to future directions of research and development. all thesis chapters will presents as follow:

- **Chapter 2**: This chapter gives general background about soft biometric presented, related works in facial soft biometric studies are discussed in addition to research direction.

- **Chapter 3**: An overview of wrinkles detection methods are presented. By focused on the state-of-the-arts methods where this research attempts to contribute

- **Chapter 4**: This chapter describes the methodology.
- **Chapter 5**: This chapter discussed an enhancement automatic wrinkles detection algorithm will be discussed in addition to evaluation of two state-of-the-art methods.
- **Chapter 6**: Here, the method which used to investigate the uniqueness of facial wrinkles is discussed.
- **Chapter 7**: Conclusion, limitation and challenges in addition to future work.

Chapter 2

Background

2.1 Introduction

This chapter presents a general discussion about soft biometric; definition, benefits, and domains of use. It also presents related works in facial soft biometric studies. Moreover, this chapter discuss facial wrinkles as soft biometric in addition to research direction.

2.2 Overview

Face recognition is considered as one of the important applications in computer vision, it is used in many important fields. Some conditions such as poor resolution, occlusion, blur, illumination and pose variation may effects on the performance of these applications Batool et al. (2013). New type of features were used by researcher to overcome the mentioned factors problems; these features are facial soft biometric. This research focuses on facial wrinkles, it investigates the discriminative power of facial wrinkles to be used as soft biometric.

Because of the rapid enhancement in imaging devices that reflected on powerful and resolution; it became possible to detect and analyze the facial features easily. Many studies are explored in the literature, Jain and Park in Jain & Park (2009) proposed to utilize facial marks like facial freckles, moles and scars to improve the facial recognition and retrieval performance using images from FERET and Mugshot database. Their experiments firstly conducted to segment and locate

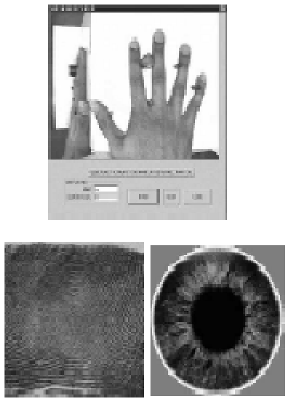

Figure 2.1: Illustrate of biometrics examples Jain et al. (2007))

primary facial features (mouth, eye, and nose) using Active Appearance Model (AAM). The second step is to detect facial marks using Laplacian of Gaussian (LoG) and morphological. Their experiments showed the performance is higher when using facial marks beside traditional facial recognition system. Furthermore, Klare et al. Klare et al. (2011) presented an application which used to distinguish between identical twins using manually annotated facial marks in addition to primary facial features. Moreover, a combination of traits such as skin, hair, eye color and the presence of glasses, beard and mustache was used by Ouaret et al. Ouaret et al. (2010) to reduce the search time in a face retrieval application.

2.3 Biometrics

Biometrics is the science of recognizing individuals based on their physical, behavioral, and physiological attributes such as fingerprint, face, iris, gait and voice Dantcheva et al. (2016). Due to need of establishing the identity of a person is becoming critical in several of applications, and, asking questions like "is she really who she claims to be?", "is this person authorized to use this facility?" are routinely being posted in a variety of applications such as commercial, governmental, and forensic applications like criminal investigation. So reliable user authentication techniques are needed, these techniques are based on biometrics. Figure 2.1 illustrate an example of biometrics.

As mentioned in Jain et al. (2004*b*), the biometric systems are classified to uni-model and multi-model biometric system; the type which is used single trait to identify individuals is called uni-model, this type can be affected by problems like noisy sensor data, non-universality and/or lack of distinctiveness of the chosen biometric trait, unacceptable error rates. Some of these problems can be overcome by the use of multi-modal biometric systems which are based on different biometric identifiers like fingerprint, iris, and face. But, such system will require a longer verification time due to numerous execution for multi biometric. A possible solution to the problem of designing a reliable system is to use ancillary information about the user like height, weight, age, gender, ethnicity, and eye color to improve the performance of the primary biometric system, these information are called soft-biometric.

2.4 Soft Biometrics

Recent researches have explored the possibility of extracting other information from primary biometric traits, like, iris, face, hand geometry, and fingerprints. The extracted information may includes personal attributes such as gender, age, ethnicity, hair color, height, weight, etc. These attributes are called soft biometric. It can be used in security applications to improve the accuracy of a primary biometric system, or can be used to generate qualitative descriptions of an individual (e.g., "young Asian female with dark eyes and brown hair"). The latter is particularly useful in bridging the semantic gap between human and machine descriptions of biometric data Dantcheva et al. (2016).

Jain et al. Jain et al. (2004*a*) defined the soft biometric as set of characteristics that gives you some information to be used in the system of individuals recognition, but these characteristics are not capable to distinguish between individuals as they are not unique and not permanent. Samangooei et al. Samangooei et al. (2008) and Reid and Nixon Reid & Nixon (2011) described it as the attributes that nicely fill the gap of describing biometric data between human and machine descriptions, also they defined it as labels that people used in describing each other. Figure 2.2 explains an example of soft biometric information that can be extracted from primary biometric.

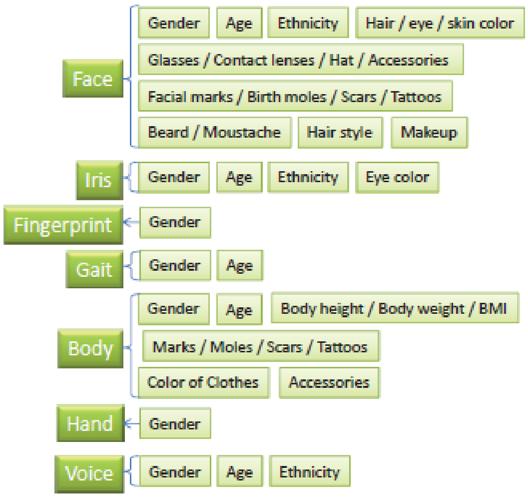

Figure 2.2: Primary biometric and extracted soft biometric Jain et al. (2004*a*))

2.4.1 Why Soft Biometrics?

As noted by Jain et al. Jain et al. (2004*b*), the soft biometric are inexpensive to compute, and can be discerned at a distance in a crowded environment, also they need not cooperation of the observed subjects. Furthermore Dantcheva et al. Dantcheva et al. (2016) was noted some benefits of soft biometric as follow: Human understandable interpretation: Soft biometric attributes almost gives description that can be easily understood by humans; for example (female, tall, old). This can be useful information in many applications such as video surveillance and police reports. Other benefit is that soft biometric attributes had robustness to low data quality: some of soft biometrics attributes can be extracted even in low environment quality figure 2.3 is an example of this benefit. Moreover, the acquisition of these attribute may not need of cooperation for observed one. Other benefit explained by Dantcheva et al. (2016), that the soft biometric attribute offer some privacy for peoples because it just provide a partial description of a person (such as “female, tall, young”).

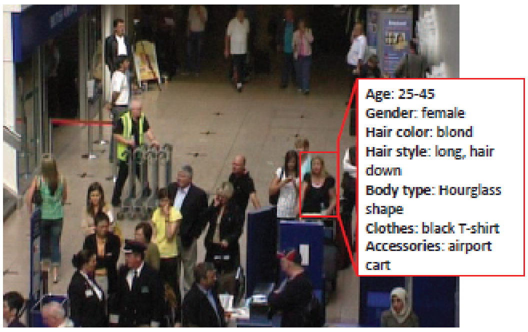

Figure 2.3: Example of extracted soft biometric attribute in crowded environment Dantcheva et al. (2016)

Table 2.1: Illustration of soft biometrics taxonomy Dantcheva et al. (2016)

Demographic Attributes	Age, gender, ethnicity, eye-, hair-, skin-color
Anthropometric and Geometric Attributes	Body geometry and facial geometry
Medical Attributes	Health condition, BMI/ body weight, wrinkles
Material and Behavioral Attributes	Hat, scarf, bag, clothes, lenses, glasses

2.4.2 Soft Biometrics Taxonomy

Dantcheva et al. Dantcheva et al. (2016) explained that it is very difficult to define standard taxonomy for soft biometrics. Table 2.1 summarizes some examples of soft biometrics taxonomy.

2.4.3 Domains of Application

Like primary biometrics that are extracted automatically and used in many applications, Also soft biometrics can be used in many applications, these applications extracted automatically one or more soft biometrics attributes. Soft biometrics can used in the area of security where the security application can locate the person based on specific attribute of soft biometrics. In human computer interaction where the person shape and data can design depends on the external appearance of the user (e.g. age, gender, skin color); and in surveillance application where suspect can be identified based on semantic descriptions; and in forensics where can be used by artists to amend the shape of victims and suspect based on pictures. Furthermore soft biometrics can be used in Electronic Customer Relationship Management (ECRM) can be used to manage customer by offering customized products and services based on age or gender. Also soft biometrics is used in age-specific access control, for example, to prevent children to access specific websites. Finally, soft biometrics like body weight/body mass index, skin abnormalities, and wrinkles can be used in health monitoring by envisioned it to use in the early diagnosis of illness, sickness prevention and health maintenance Dantcheva et al. (2016).

Moreover, the domains of application that used soft biometrics can be classified into three classifications: a) Uni-Modal System: this type of application used single soft biometrics attribute (e.g. using of gender, age attributes in a gender-personalized advertising campaign) Dantcheva et al. (2016); b) Fusion with Primary Biometrics Traits: is the second classification, the goal of this type of application is to improve the recognition accuracy of biometric system as used in Jain et al. (2004*b*); and c) Search Space Reduction: as explained by Kumar et al. (2008) in this classification the soft biometric can be used to speed up the search process in large biometric databases by filtering the subject. Also, Kumar et al. Kumar et al. (2008) proposed a number of attributes such as gender, age, hair and skin color for efficient filtering of face databases.

2.5 Soft Biometrics Attributes

Different soft biometrics attributes can be used in many applications, in this section some of these attributes along with studies that used it will be explained.

2.5.1 Gender Estimation

Loth and Iscan Loth & İşcan (2000) explained in their forensic literature review that the chin, jawbone, and pelvis is the most significant indicator of the person's gender; these shape-based features provide 91-99% classification accuracy in juveniles. But they also argued that there is no single feature of skeletal that definitely reveals the evidence of sexual dimorphism, and that there is in fact a cross-gender metric overlap of up to 85% which can be attributed to environmental influences and pathologic conditions, such as occupational stress and diet. But the forensic experts in Iscan & Steyn (2013) argued that the gender determination near 100% can be achieved by visual examination of the whole of the skeleton. However, automatic gender recognition from biometrics data remains difficult and affected by other soft biometrics like race and age.

2.5.1.1 Gender From Face

Dantcheva et al. Dantcheva et al. (2016) explained that the process of gender recognition from face consist of feature extraction and pattern classification steps, the feature extraction step considered as challenges in the face recognition process, to perform this step different types of strategies have been attempted. Sun et al. Sun et al. (2002) in their strategy used a genetic algorithm to select the eigenfeature. Some approaches focus on specific facial features, such as an approach that focused on eye brow and jaw region as discussed by Zhang et al. Zhang et al. (2011). Besides the difficulty of feature selection, another challenge comes from unconstrained setting like the changes in illumination, pose, and others that affect on the face image.

2.5.1.2 Gender From Fingerprint

This type of gender classification received attention in forensic anthropology, it used as a tool to reduce the search space about someone. This type of classification offers distinguishes between male and female fingerprint. As explained by Nigeria (2012) the differences between the fingerprint include the ridge-thickness to valley-thickness ratio (RTVTR), the ridge count (the average ridge count is higher in males than in females), and the count of white lines. This classification was record very good recognition rate as used in Gupta & Rao (2014) Gnanasivam & Muttan (2012).

2.5.1.3 Gender From Iris

Gender classification from iris inspired originally by Thomas et al. Thomas et al. (2007). They used combination of texture features and seven geometric features (horizontal, vertical, and Euclidean) distances between the iris center and pupil center to apply the classification. The classification was performed by bagging 100 C4.5 decision trees, they used 28000 iris images as dataset and the classification accuracy was 75%. This work was improved to 80% as classification accuracy when considering only Caucasian subjects.

2.5.1.4 Gender From Body

Dantcheva et al. Dantcheva et al. (2016) explained that the body of person has a number of cues can be used to distinguishing the gender, these cues include body sway, waist-hip ratio, and shoulder-hip ratio, females have a distinct waist-to-hip ratio and swing their hips more, whereas males have broader shoulders and swing their shoulders more. At the same time, there are some features impacted negatively on the gender classification from bodies such as clothes, background, and shoes. Another feature can be used to classify gender from the body is gait energy image (GEI) Shan et al. (2008) which is computed from the human silhouette is extracted and a statistical feature - namely an average silhouette. Many algorithms are developed and they were achieved high classification accuracy ratio for example Shan et al. Shan et al. (2008) achieved 97.2% they used GEI and facial features.

Another biometrics attributes can be used for gender classification like gender classification from hand can be found in Kanchan and Krishan Kanchan & Krishan (2011) and Scheuer and Elkington Scheuer & Elkington (1993); also gender classification from speech can be found in Childers et al. Childers & Wu (1991).

2.5.2 Age Estimation

Many facial features are affecting on the facial age; holistic face features like face shape and skin texture, local face features like the area of eyes, nose, and forehead, and related configuration like symmetry Rhodes (2009). Main challenge in age estimation is that previous mentioned features a function of any unknowns, including living style, genetics, health condition, working environment, and sociality.

2.5.2.1 Age From Face

As explained by Dantcheva et al. (2016) many approaches used to determine the age of person from his face: geometric based approaches is one of these approaches, this approach based on the cranio-facial development, in other words, it determines the age from the ratios between different anthropometric measurements as employed by Ramanathan and Chellapa Ramanathan & Chellappa (2006); they used 8 distance measure ratios to model age progression, their model provide improvement in face recognition performance for ages up to 18 years from 8 to 15%. This approach has some drawbacks, the model that based on anthropometric is better to differentiating between infants and adults. In addition to the measurements and their associated ratio can be determined from 3D or frontal images. Furthermore, many studies was conducted to estimate the facial age from depends on the facial wrinkles as explained in Ng et al. (2014*a*).

2.5.3 Race Classification

The traditional definition of race is related to biological factors and often refers to a person's physical appearance corresponding to traits such as skin color, eye color, hair color, bone/jaw structure, face and body shape, and other traits. Dantcheva et al. (2016).

2.5.3.1 Race From Face

As explained by Dantcheva et al. Dantcheva et al. (2016), race classification go throw many steps: first step is feature extraction which is extracted from feature representation module, then classification module is used to classify the race in second step; the classification module used extracted features from first step and categorize it into discrete number of race classes.

Many approaches can be used to classify the race from face: approaches based on chromaticity or skin tone, these approaches have been employed as primary feature for race classification, see Xie et al. Xie et al. (2012). Also other approaches that can be used for race classification are approaches based on global features or holistic representation can be found to preserve interrelation between facial regions, Lu and Jain Lu & Jain (2004) employed an LDA-based algorithm to classify 263 subjects into 2 categories (Asian and Non Asian) obtaining a success rate of about 96%; approaches based on local feature descriptor representation Hosoi et al. Hosoi et al. (2004) obtained 94% as accuracy for race classification by using Gabor Wavelet Transformation and retina sampling, along with a SVM classifier. On a database containing 771 Asian, 774 European and 446 African subjects; finally hybrid approach was presented by Ding et al. Ding et al. (2013) that used local texture and global shape features, resulting in accuracies of up to 98.3%.

2.5.3.2 Race From Iris

Qiu et al. Qiu et al. (2006) showed that the geometric characteristics of the iris exhibit significant differences across races, their work considered a binary classification problem (Asian vs. non Asian), and employed the CASIA database with 2400 images for the Asian subjects, while for the non Asian subjects it employed the UPOL database6 with 384 images of 64 subjects and the UBIRIS database Proenca et al. (2010) with 1198 images of 240 subjects. Using AdaBoost, the work recorded an accuracy of 85.95%.

2.6 Facial Wrinkles as Soft Biometrics

Batool and Chellappa Batool et al. (2013) tried also to prove that the facial wrinkles can be used as soft biometrics, they observed that the application used human figures to produce portrait drawings, sketching, caricature, was included set of wrinkles which were specific to the person, so, from this point they derived their motivation to ask about the ability of the set of facial wrinkles that can be used as soft biometrics. Pictures of famous person are downloaded from the internet and used in their experiments to answer their question.

Many processes have been used in this study, they did their experiments on forehead facial wrinkles. Hausdorff distance and curve-to-curve correspondences have been used to find the similarity between every two persons' curve pattern, also bipartite graph matching algorithm has been introduced to discover the correspondences between curves from two pattern.

2.7 Research Direction

While automatic wrinkles detection algorithms are strong and achieve high accuracy rate as explained in chapter 3 (related work), most of them are focused on detecting the facial wrinkles for the area of forehead, but there are no comprehensive studies tried to detect the wrinkles for entire facial area, and there is only one study Batool et al. (2013) that analyzed the efficiency of using facial wrinkles similar to basic biometric (fingerprint, voice, iris, and DNA) to identify the human, and they tried to answer the question ”is the facial wrinkle unique”. Batool and Chellappa in Batool et al. (2013) achieved good result, but their study just used wrinkles in forehead area in addition that they are not used large dataset to prove their work. If the uniqueness of facial wrinkles is achieved, so use it as soft biometric is being potential.

2.8 Summary

From the illustrated research direction; the investigation of the discriminative power of facial wrinkles to be used as soft biometric using entire facial wrinkles will be explained. The starting point will be with facial wrinkles and then used the detected wrinkles and answer our research question about soft biometric.

Chapter 3

Related Work

3.1 Introduction

In this chapter, an overview of wrinkles detection methods are presented. The focus is on the state-of-the-arts methods where this research attempts to contribute. Section 3.2, introduction about facial wrinkles. Section 3.3, discussed the applications where facial wrinkles detection plays an important role. Section 3.4, review in the earlier wrinkles detection methods (manual wrinkles detection algorithms). Section 3.5, comprehensive review of automatic wrinkles detection algorithms included state-of-the-art methods. Section 4, chapter conclusion.

3.2 Overview of Facial Wrinkles

Factors like aging and frequent exposure to solar ultraviolet (UV) radiation are affecting the face features. These factors contribute to change of facial skin, and the overall face shape will be affected by these changes in addition to features change of the face: folds, wrinkles, and lines will be appear and become more obvious with age Phimoltares et al. (2007).

Physiologically, many facial features are changes as people getting older, where facial wrinkle is one of these features. It appears and become more obvious with age. These wrinkles are changed based on the skin nature and muscle contraction Boissieux et al. (2000). Wrinkles can be defined as creases or small furrow in facial skin that caused by expressions or age. Ekman et al. Ekman & Friesen (1977) described wrinkles as a line with depth and sometimes the line have a width more than surface line. In some faces, the wrinkles may be temporary appear with certain actions, while other faces may show permanent wrinkle and it will be deepen with certain actions. In 2D images, the wrinkles are affecting the skin; it creates deep creases and sometimes creates curvature in the skin surrounding, this curvatures will affect the overall facial skin Ng et al. (2015*a*). The wrinkles characteristics can be described using two major factors: one of them used to define the location of wrinkles curve lines, this called furrow or macro, and the other one is bulge, which is used to give curved surface shape Wu et al. (1996).

From Boissieux et al.'s perspective Boissieux et al. (2000), there are two types of wrinkles: the wrinkles appear due to facial expression and the permanent wrinkle. The former is called expressive wrinkles where it considered as temporary wrinkles, but may become permanent with time. The latter is permanent wrinkles which are appearing with age. Furthermore, as mentioned in Piérard et al. (2003), the wrinkles can be divided into four types according to wrinkles pathogenesis and histological conditions. First type is atrophic; this type of wrinkles appear as parallel lines and they disappear when skin is put under transversal tension. Second type is elastotic; this type is appearing when the skin is exposing to sun and it considered permanent. Third type is expressional, as mentioned above, it is temporary wrinkles, but it may become permanent lines. Fourth type is gravitational; it resulted from gravitational forces inducing folding and sagging of skin which has lost its turgidity

Human eye can detect wrinkles easily, but it is a very difficult task to detect wrinkles automatically using image processing techniques. This is due to the wrinkles shape is varying according to ethnic group, gender, age, and personal life style. Also it depends on the image quality that was affected by image acquisition environment Mawale & Chaugule (2016).

Many different approaches in detecting the features changes on the face exist, including detection of facial wrinkles. Earlier work in wrinkles detection was proposed by Loden et al. Lodén et al. (2007), they used silicone to produce the facial wrinkles by making replica using this silicone and made the measurements depends on it. But these old studies were not efficient enough, because it is very difficult to get silicone replicas same as the actual skin morphology. In 2014, Ng et al. Ng et al. (2015*b*) proposed Hybrid Hessian Filter (HHF) to detect and quantify the facial wrinkles automatically, their algorithm recorded very good results in detecting wrinkles.

As automatic wrinkles detection became an important step in many applications, so, the aim is to provide a review on manual and automatic state-of-the-art wrinkles detection techniques to provide a breadth and depth analysis

3.3 Applications of Wrinkles Detection Algorithm

Facial wrinkles are very important facial feature that present on aging faces. Accurate wrinkles detection plays an important step in several image based application, like age estimation Choi, Tak, Rho & Hwang (2011)Kwon & da Vitoria Lobo (1999), and synthesis Ramanathan & Chellappa (2008), face modeling Bando et al. (2002), facial expression recognition Huang et al. (2010), and it can be used as soft biometric Batool et al. (2013).

In the **age estimation and synthesis** application: different parts of human body is being affected by human age under several environmental and biological factors. The wrinkles are the obvious change that occurs on the face according to the age. So wrinkles detection is main stage in many studies of age estimation Hayashi et al. (2002) Choi, Lee, Lee, Park & Kim (2011) Ng et al. (2014*b*) Dehshibi & Bastanfard (2010) Jana et al. (2015). Also wrinkles can be added to facial image to show how it can affect on the face in case there are some changes occurs like gain weight or loss weight as mentioned in Ramanathan & Chellappa (2008).

In **the face modeling** application, Bando et al. Bando et al. (2002) used fine and large scale wrinkles to model the human skin including facial skin, they found that the wrinkles are adding more realism on the facial skin.

In **facial expression recognition** application, Huang et al. Huang et al. (2010) claimed that different types of wrinkles like forehead, nasolabial, dimples, chin furrows and eye pouches are important features that can reflect individual's emotion. In their experiments they proved that nearly 70% of expressions can be differentiating by skin wrinkles and slide view profile. This result contributed to increase the overall recognition rate. So the facial wrinkles can be used as one of the features that can increase the recognition rate. Many studies used wrinkles for this type application as mentioned in Park & Bien (1999) Huang et al. (2010) Yin & Basu (2001).

In **soft biometric** application, soft biometric is a feature that been used to complement the primary biometric features, such as fingerprint, face, iris, and hand geometry, to enhance the performance of a primary (hard) biometrics system Fu et al. (2010). The researcher tried to investigate the discriminative power of using wrinkles as soft biometric as proposed by Batool and chellappa in Batool et al. (2013). In addition to all these applications the facial wrinkles detection is important step in **facial retouching** application as mentioned in Arakawa (2004) Ohchi et al. (2010) Batool & Chellappa (2015).

3.4 Facial Datasets

Different types of face datasets are available, but only a few of them are appropriate to be used in developing an accurate wrinkles detector, here are the four most popular state-of-the-art datasets:

3.4.1 FG-NET Dataset

FG-NET is a big dataset consists of 1002 images taken from 82 different subjects with ages ranged between 0 to 69 years old; these images were collected from albums using scanner, most of the dataset images were 40 years Panis et al. (2015). This dataset is not clear and the images resolution was different, so it is not a good choice for wrinkles detection algorithm. The dataset images comes along with many information like age, and each image had several copies with different age, so it can be used for age estimation application as used in Ng et al. (2014*b*) Han et al. (2013).

3.4.2 Bosphorus Dataset

Bosphorus is expression dataset contained 3D and 2D faces Savran et al. (2012). This dataset is highly resolution dataset because it collected under controlled environment from different 105 subjects, ages among most of them were ranged

Table 3.1: Summary of the state-of-the-art face datasets.

Dataset	Number of Images	Number of Subjects	Age Range
Bosphorus	4666	105	25 - 35
FG-NET	1002	82	0 - 69
MORPH	55,134	13,000	16 - 77

between 25 and 35. The dataset considered as excellent choice for wrinkles detection algorithms, it used by Ng et. al in Ng et al. (2015*a*)Ng et al. (2015*b*) and it recorded very good results.

3.4.3 MORPH Dataset

Morph is a large dataset consisted of 55,134 images collected from more than 13,000 individuals with ages ranged between 16 to 77 years old. The dataset is available for a researcher who works on age progress applications. Morph also considered as low resolution dataset like FG-NET, because it collected from scanning photographs, but it contained older age photos, so it may considered a good choice for wrinkles detection algorithms if the resolution adjusted and the noise removed Albert & Ricanek Jr (2008).

3.5 Performance Measurement for wrinkles detection algorithm

Two measurements to evaluate the performance of the wrinkle detection algorithm mentioned in the literature, which are Jaccard Similarity Index (JSI) that was first used by Ng et al. Ng et al. (2015*b*) in wrinkles detection to evaluate the performance of their algorithm. Another measurement is mathematical evaluation setup that proposed by Batool and Chellappa Batool & Chellappa (2012). JSI is the most commonly used method in medical imaging analysis, this techniques originally introduced by Paul Jaccard Jaccard (1901), which also known as Jaccard similarity coefficient or intersection over union. The mathematical form of JSI is:

$$JSI(A,B) = \frac{A \cap B}{A \cup B} \tag{3.1}$$

where A and B are two compared images.

Second method was proposed by Batool and Chellappa Batool & Chellappa (2012), they proposed evaluation setup to assess the performance of their wrinkles detection algorithm. Three terms were used in this evaluation setup: detected, original and well-localized. The term detected considered the output wrinkles from the algorithm, while the term original refer to the original wrinkles those were hand-drawn by user, and well-localized term refer to wrinkles that detected at correct locations. Detected wrinkle is considered well-localized if it is lies within the distance of m pixels (m=3) from the hand-drawn wrinkles. They used morphological dilation with margin m to define the overlap area. Detected wrinkle is considered well-localized if it lies within the overlap area.
They proposed the following ratios for evaluation:

a. Detection Ratio (r_{detect}): The ratio of the total length of original wrinkle within the overlap region of detected wrinkles to the total length of the original wrinkles.

$$r_{detect} = \frac{\sum_{n_w} L_{overlap}}{\sum_{n_w}(L_{overlap}+L_{miss})} \tag{3.2}$$

b. False Alarm Ratio (r_{false}): The ratio of the total length of falsely detected wrinkles to the background area with no wrinkles ((S) represents the measure on image space).

$$r_{false} = \frac{\sum_{n_D} L_{false}}{v(s) - \sum_{n_w} L_{original}} \tag{3.3}$$

c. Miss Ratio (r_{miss}): The ratio of the total length of missed original wrinkles to the total length of original wrinkles.

$$r_{miss} = \frac{\sum_{n_w} L_{miss}}{\sum_{n_w}(L_{overlap}+L_{miss})} \tag{3.4}$$

where $r_{miss} = 1 - r_{detect}$ and n_w, n_D are the total number of hand drawn and detected wrinkles respectively.

3.6 Manual Wrinkles Detection

Wrinkles considered as important facial features that affects on human age estimation, so it is important in several facial applications related to aging applications like age estimation Choi, Tak, Rho & Hwang (2011)Kwon & da Vitoria Lobo (1999) and synthesis Ramanathan & Chellappa (2008), facial expression recognition Huang et al. (2010), face modeling Bando et al. (2002), and can be used as soft biometric Batool et al. (2013).

Earlier wrinkles detection studies used manual techniques to detect facial wrinkles and other facial features. Using silicone material is one of these manual techniques, the silicone material is used to produce skin replica, then use this replica to detect the wrinkles as mentioned in Lodén et al. (2007) Hatzis (2004) Vargiolu & Zahouani (2004). The drawbacks of this approach represent in the difficulty to produce silicone replica same as actual skin morphology, in addition to the silicone material problem itself. Also the cosmetics science has some techniques for facial wrinkles detection, one of them is using three dimensional optical profilometers based on digital fringe projection technology for in vivo measurement of skin morphology as mentioned in Jaspers et al. (1999)Rachel & Jamora (2003), the limitation of this approach represents in equipment resolution.

Another type of manual wrinkles detection is human observation as proposed by Mark et al. Mark et al. (1980), their work was examination of several feature's influence on human age judgments by drawing the profiles of different male's ages, then to determine the age of drawing wrinkles faces.

Casanova et al. Aznar-Casanova et al. (2010) presented a study to determine if the facial age is affected by wrinkles, their study composed of two experiments: In experiment I; categorical age judgments for males and females had been made. This experiment examined by ninety nine volunteers (male and female) segmented to three age categories (preadolescents, young adults, and middle-aged adults). The result of this experiment indicated that the influence to age will be greater if the number of wrinkles and the depth furrows are increased. In experiment II, the participant compared between each pair of faces to determine the similarities of features that had more effects on the face. The results showed that the wrinkle's number had more influence on age of the face than the wrinkle type.

Batool and Chellappa Batool et al. (2013) conducted a study to determine if the facial wrinkles could be used as soft biometrics, their experiments based on manual wrinkles detection.

3.7 Automatic Wrinkles Detection

The great improvement in computer vision motivates researchers to spot light on multiple algorithms like automatic wrinkles detection algorithm that considered as important step in many applications like age estimation application Choi, Tak, Rho & Hwang (2011), where fine lines and wrinkles play an important role Batool & Chellappa (2015). Kown and lobo Kwon & da Vitoria Lobo (1999) tried to show how wrinkles affect on human age based on three age groups; which are babies, young adults, and senior adults. Firstly, they detected the primary features of each face: like eyes, nose, mouth, chin, and virtual top of the head, the output was distinguished the baby from others. Secondly, the facial wrinkles was detected using wrinkles geography map, then the output distinguished the seniors adults from younger adults categories. On the other hand, Choi et al. Choi, Tak, Rho & Hwang (2011) proposed wrinkle representation scheme to estimate age of the skin by construct skeleton consisted of most features related to the wrinkles using watershed algorithm to represent the wrinkles on skin of the image.

The above mentioned studies tried to identify the effect of facial wrinkles on human age, but there are researcher just focused on developing algorithms to detect the wrinkles automatically. Table 2 and Figure 1 depict the development of automatic wrinkles detection methods over the past 10 years in chronological order. Cula et al. Cula et al. (2013) developed automatic wrinkles detection algorithm, it was based on orientation estimation and the frequency of elongated spatial features. They used a set of facial images that was clinically validated to detect the wrinkles that appear on the forehead, the wrinkle scale for these images was varying from 0 (no wrinkle) to 11 (most severe wrinkles). The algorithm was tested using two cases: First they combined the wrinkles depth information with the wrinkles length information, and second they separated the wrinkles length information from the wrinkles depth information. The algorithm performed better in the first case. This algorithm considered as one of the earliest automatic wrinkles detection algorithms in 2D images, but it has some limitations in wrinkles localization, and in distinguishing wrinkle from image noise like hair, scars or illumination.

After Cula et al. Cula et al. (2013), other researchers tried to improve the quality of automatic wrinkles detection methods. Ng et al. Ng et al. (2015*b*) developed a novel method for automatic wrinkles detection, it called Hybrid Hessian Filter (HHF). HHF is an algorithm for automatic wrinkles detection in 2D facial images. The algorithm based on Hessian matrix and directional gradient which is used to detect the facial wrinkles by compute this matrix to all pixels for each image, the Hessian Matrix maximum eigenvalues indicates whether or not the point is a part of a ridge regardless this ridge's orientation. Each point (x, y) field's second derivative component measures eigenvalues (independent vector), the more small eigenvalues, the more field's corresponding eigen-direction change a little and vice versa. HHF used 100 random selected images from Bosphorus dataset Savran et al. (2012), from these images, researcher used forehead area, so they cropped the images manually with rectangle selector. The algorithm was showed better result compared to other methods such as Cula's method Cula et al. (2013), it considered outperformed state of the art methods with average JSI of 75.67%. According to this result, HHF considered as a strong wrinkles detection algorithm compared to other state-of-the-art methods, it had a good result regarding wrinkles localization in addition to increasing the correctly detected wrinkles' number. HHF recorded very good result for forehead especially medium and coarse wrinkles, but, more effort is needed to improve this algorithm, it neither detect wrinkles on other facial regions, nor detect vertical lines.

As an extension to HHF, Ng et al. Ng et al. (2015*a*) developed Hessian Line Tracking (HLT), tried to overcome the problems of previous automatic wrinkles detection methods. HLT is an algorithm for automatic wrinkles detection in 2D facial images, it composed of hessian seeding and directional line tracking. HLT executed in many steps; firstly HHF was used to extract the seeds and then the optimum pixels for starting point determined. Line tracking was used to determine each pixel belongs to wrinkle line. Then post processing using median and directional filter in addition to area threshollding was applied to remove the noise (outlier). The algorithm was validated using 100 manually cropped forehead faces from Bosphorus dataset Savran et al. (2012). when HLT compared to benchmark algorithms like Cula's algorithm Cula et al. (2013), Frangi Filter (FRF) Frangi et al. (1998) and HHF Ng et al. (2015*b*) it performed better result with accuracy of 84.00%. HLT considered a strong detector of forehead wrinkles in 2D images, add to that, the algorithm has ability to explore the curve and valley pattern in order to wrinkle connectivity, but it needs more enhancement to detect other facial wrinkles and vertical lines.

More recently, Ng et al. Ng et al. (2017) have proposed to use wrinkles as complementary features for face age estimation. They proposed two new methods in this study, Multi-scale Wrinkle Patterns (MWP) used as a feature representation for facial wrinkles and Hybrid Ageing Patterns (HAP) used as a new feature representation for face age estimation. HLT Ng et al. (2015*a*) was used as wrinkles detector in MWP after tested against state-of-the-art wrinkles detection methods (HHF Ng et al. (2015*b*),Cula's method Cula et al. (2013), and Batool's method Batool & Chellappa (2015)) to detect whole facial regions. Lastly HAP is used to train the SVM to estimate the facial age. Three state-of-the-art dataset (FERET Phillips et al. (1998*a*), FG-NET Panis et al. (2015), and Morph Albert & Ricanek Jr (2008)) were used to assess the performance of HAP, it recorded good result with a MAE of 3.68 ($\pm$2.98) on MORPH, 3.02 ($\pm$2.92) on FERET, and 5.66 ($\pm$5.88) for FG-NET.

Batool and Chellappa proposed many algorithms for facial wrinkles detection Batool & Chellappa (2012)Batool & Chellappa (2014)Batool & Chellappa (2015). In 2012, they proposed a novel modeling technique for wrinkles, based on spatial marked point processes (MPP). They considered the wrinkles as sequences segments of line that appear as stochastic spatial arrangements at the aging face, so intensity gradients were used to detect probable line location, then probability model was used to constrain properties of the line segment. In addition, Batool and Chellappa used the Reversible Jump Markov Chain Monte Carlo (RJMCMC) algorithm to MPP sampling that used to localize the wrinkles. The model could allow the incorporation of wrinkles, also the detected wrinkles as spatial curve patterns could be incorporated in biometric applications. Finally, the presented detection algorithm could enable the use of a large set of images with baseline wrinkles for that purpose Batool & Chellappa (2012). This algorithm has the ability to detect clear and deep wrinkles, but it failed to detect other wrinkles' types. It also focused on forehead and horizontal wrinkles, it neither detect other facial region, nor detect vertical wrinkles.

In 2014, Batool and Chellappa developed a new algorithm Batool & Chellappa (2014) to detect facial wrinkles and imperfections that could be used for facial retouching applications. The algorithm was used to detect forehead wrinkles. Two types of features from the forehead area were conducted using texture orientation and Gabor filter. Firstly they used Gabor Filter to highlight the intensity gradients in any directions, then orientation field highlighted the discontinuities in the normal flow of skin texture. After that they merged highlighted features using Gaussian Mixture Models (GMM) and Markov random field representation. The result of this algorithm is better than the previous algorithm developed by same researchers, but it has limitation in detecting complex wrinkles, moreover, the algorithm did not address false positive value.

A year later, Batool and Chellappa developed another wrinkles detection algorithm, which they called it as fast wrinkles detection algorithm Batool & Chellappa (2015). The algorithm used Gabor Filter Bank to extract the features of images, it also used image morphology to incorporate geometric constraints that used to localize curvilinear shapes of wrinkles at image sites. To validate the algorithm, researchers used two types of datasets; low and high resolution (some images from FG-Net and the other 125 high resolution images of famous persons downloaded from the Internet). The experiments showed that the proposed algorithm is faster and gives better results for wrinkles localization in addition to decrease the false positive detection compared to their previous algorithm in Batool & Chellappa (2012).

This chapter tried to shed light on the most important and state-of-the-art automatic wrinkles detection related to the last ten years. Wrinkle detection went through many stages, started at manual wrinkle detection till it reached automatic wrinkle detection. The enhancement within algorithms used to automatic wrinkle detection accompanied all automatic wrinkle detection stages led to great algorithms like HHF Ng et al. (2015*b*) and HLT Ng et al. (2015*a*), but it needs more improvement, all the above algorithm focused to detect horizontal lines in forehead region, while the wrinkles can be appeared as vertical lines on other facial regions.

Osman et al. Osman et al. (2017) conducted a study to investigate the effects of smoking on whole facial wrinkles using social habit face dataset Alarifi et al. (2017*a*). Modified HHF was proposed to detect the facial wrinkles; this algorithm is used to detect horizontal and vertical wrinkles. The face was splitted into 10 regions Ng et al. (2015*c*), then the algorithm was applied to them separately. The result showed that the density of wrinkles for smokers in the regions around the mouth was significantly higher than the non-smokers, at p-0value of 0.05. This algorithm considered as the first method that tried to detect vertical line, but it did not validated using state-of-the-art dataset. So, more improvement is needed. Furthermore Yap et al. Hoon Yap et al. (2018) extended HHF by introduced multi-scale filter that used to extract coarse and fine wrinkles for all facial region. This method used in their automated facial wrinkles annotator, which presented to overcome the difficulty of manual annotation. The method showed good result when evaluated against manual annotation using their in-house and FERET dataset.

The transient wrinkles, like expression wrinkles did not have sufficient study, due to the nature of wrinkles' types (shape complexity and diversity), so, most studies focused on permanent wrinkles detection like age wrinkles which have usually linear shape. In 2017, Xie et al. Xie et al. (2017) proposed a novel transient wrinkle detection algorithm and its application for expression synthesis. In this algorithm, edge pair matching and active appearance model (AAM) were used for wrinkle structure location, in addition to support vector machine (SVM) which used for wrinkle classification. Compared to state-of-the-arts algorithm, the algorithm yield complete and accurate wrinkle centers, also the expression synthesized by the improved wrinkle mapping was much more realistic.

All studies above used one of different approaches that are used for wrinkles detection. The popular one is snake-based approach, this approach uses active contour map to localize and initialize the wrinkles as mentioned in Choi, Tak, Rho & Hwang (2011) Batool & Chellappa (2012). Also filter-based is one of the approaches that are used to detect the wrinkles as mentioned in Cula et al. (2013)

Table 3.2: A summary of Automatic Wrinkles Detection Algorithms.

Year	**Author**	**Dataset**	**Area of Detection**	**Accuracy and Metrics**
2012	Batool and Chellappa Batool & Chellappa (2012)	images from internet	Forehead Wrinkles	Quantitative evaluation
2013	Cula et al. Cula et al. (2013)	100 clinically gradedfacial images	Forehead Wrinkles	Quantitative evaluation
2014	Batool and Chellappa Batool & Chellappa (2014)	images from internet	Forehead Wrinkles	Quantitative evaluation
2014	Ng et al. Ng et al. (2015*b*)	100 images from Bosphorus	Forehead Wrinkles	72.67% using JSI
2015	Batool and Chellappa Batool & Chellappa (2015)	FG-Net, Images from internet	Forehead Wrinkles	Quantitative evaluation
2015	Ng et al. Ng et al. (2015*a*)	100 images from Bosphorus	Forehead Wrinkles	84.00% using JSI
2017	Omaima et al. Osman et al. 2017	Social habits dataset	Whole Face	P-value of 0.05
2017	Xie et al. Xie et al. (2017)	CK+ database	Different Facial Regions	JSI with 0.52%
2018	Ng et al. Ng et al. (2017)	Morph, FERET, FG-NET	Whole Face	MORPH 3.68 MAE

Ng et al. (2015*a*) Ng et al. (2015*b*), this approach contributes in developing new algorithms which have good affect on wrinkles detection field.

3.8 Summary

A survey on the manual and automatic wrinkles detection techniques was presented in this chapter including state-of-the-art methods that recorded good results for automatic wrinkles detection. Although there were some methods achieved very good results like Gabor Batool & Chellappa (2015), HHF Ng et al. (2015*b*) and HLT Ng et al. (2015*a*), but these research field need more enhancement. Existing wrinkles detection algorithm are focusing on the forehead wrinkles detection Batool & Chellappa (2015) Ng et al. (2015*b*), however, the wrinkles are important to many applications like age estimation and soft biometric. While there are methods just focus on detecting the horizontal lines, it is important to consider the vertical lines in some facial regions. So, it is better to detect wrinkles (vertical and horizontal) for all face rather than just forehead wrinkles. Another factor that can affect on the performance of detection is the dataset. Existing methods work very good with faces that contain medium and coarse type of wrinkles, but fine lines still caused a problem. Moreover, the methods of machine learning and deep learning are not widely used in this type of algorithm, except Xie et al. (2017) where they used machine learning. This research direction may add some progress in the automatic wrinkles detection algorithm.

Chapter 4

Research Methodology

4.1 Introduction

In previous chapters a necessary background regarding this work on winkled detection algorithm and using facial wrinkles as soft biometric were described. In this chapter a general look of the methodology which is used in this thesis is explained. The Figure bellow summarize the thesis methodology.

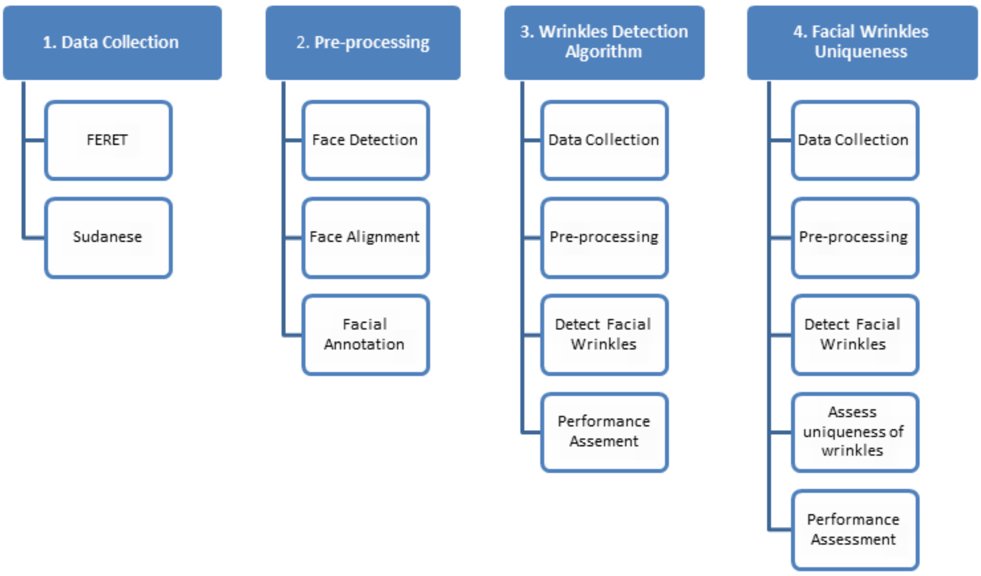

Figure 4.1: Thesis Methodology Steps

4.2 Data Collection

There are several state-of-the-art facial datasets that can be used to evaluate our proposed methods as mentioned in chapter 2, two of them (FERET and Social habits datasets) have been used in experiments, In addition to new Sudanese dataset, a dataset that has been collected from Sudan.

4.2.1 FERET Dataset

FERET is a large dataset consists of two categories; one of them is used for development, so it is available for researcher, while other category is isolates and reserved for test the facial recognition algorithm Phillips et al. (1998*a*). When compare the resolution of FERET dataset to FG-NET, FERET is considered better resolution than FG-NET because it collected under controlled environment. It used by Ng et al. Ng et al. (2015*b*) to assess the performance of their algorithm for wrinkles detection.

4.2.2 Social Habits Dataset

Alarifi et al. Alarifi et al. (2017*a*) introduced social habits dataset, it is an ongoing collection of high quality images of faces with the social habit of the participants recorded. The dataset consists of 164 images of participants (107 female, 56 male, and one transgender) their age range between 18 to 92 years old.

4.2.3 Sudanese Dataset

Sudanese dataset is a new dataset collected from Sudan to test our wrinkles detection method and facial wrinkles as soft biometric method using new type of skin. This dataset is collected under normal environment without further control or preparation; it was taken in different places under normal light. The dataset consists of 1287 images collected from 136 subjects; (130 male and 6 females) and their ages range between 16 and 80, for each subject there are 7 to 10 images with different expression. A questionnaire that includes personal data, smoking status along with no objection to use participants' information and photos has been distributed. The images were taken using Cannon EOS 600D with flash. Figure 4.5 depicts samples of Sudanese dataset.

Figure 4.2: Samples of Sudanese dataset

4.3 Preprocessing

This phase includes many subphases. The process starts with face detection and alignment, then manual annotate the wrinkles on the face by hand to construct ground truth has been done.

4.3.1 Face detection

The methodology started with facial detection which performed using freely available techniques called Face++ detector Zhou et al. (2013) that used utilized deep learning approach to detect the face. 88 landmarks were used as total points for facial image, 24 points of them for outside face or contour, and the other 64 points for inside regions (mouth, nose, and eyes).

4.3.2 Face alignment

For face alignment, triangulated mesh had obtained using Delaunay's method Rebay (1993) on the mean shape; (the points that image should be aligned according to it), after that, mean shape created to all facial images. Figure 5.1 represents the output from this step.

Figure 4.3: Selected samples of images from FERET dataset after alignment phase

4.3.3 Wrinkles Detection

In this step, face template or mask used with ten predefined wrinkles regions with fixed coordinates for mouth and eyes Ng et al. (2015*c*). The mask divided into 10 regions which represented as: forehead, glabella, upper eyelids, crows feet (or eye corners), lower eyelids (or eyebag), cheeks, nasolabial grooves (or nasolabial folds), upper lips, marionette and lower lips, as explained in figure 5.2. Each facial image was normalized to the mask by using piecewise affine warping Cootes et al. (2001). Finally, the wrinkles patterns for ten regions were constructed using proposed method.

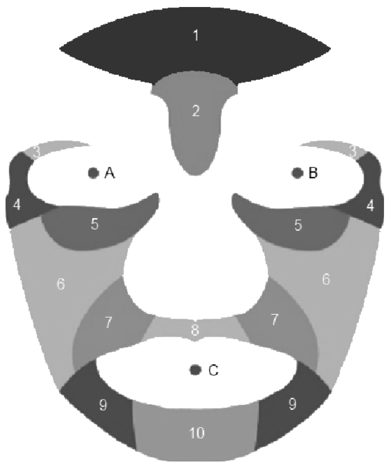

Figure 4.4: Facial mask with ten regions as defined by Ng et al. (2015*c*)

4.3.4 Manual Annotation

According to batool and Chellappa Batool & Chellappa (2012), it is easier to generate the ground truth by hand labeling, so the same concept is used for our experiments. Manually annotate the selected images from two dataset and used it as ground truth to compare the output of algorithms depends on it.

4.4 Automatic Wrinkles Detection Algorithm

In this phase two automatic wrinkles detection algorithms have been proposed, first algorithm modifying existing automatic wrinkles detection algorithm Hybrid Hessian Filter (HHF) Ng et al. (2015*b*) has been proposed. Also the researcher proposed enhancement wrinkles detection algorithm. More details about two algorithms in chapter 5.

4.5 Assessment of Facial Wrinkles Uniqueness

Here new algorithm to investigate the uniqueness of facial wrinkles using Modified Hausdorff Distance (MHD) has been proposed. More details about the algorithm in chapter 6.

4.6 Performance Assessments

After developed our methods different measurements to evaluate the performance of it have been used. Here is explanation of the measurements that are used.

4.6.1 Jaccard Similarity Index (JSI)

JSI is considered as the most commonly used method in medical imaging analysis, this techniques originally introduced by Paul Jaccard Jaccard (1901), which also known as Jaccard similarity coefficient or intersection over union. this measurement has been used to evaluate the performance of automatic wrinkles detection algorithms. The mathematical form of JSI is:

$$JSI(A,B) = \frac{A \cap B}{A \cup B} \tag{4.1}$$

where A and B are two compared images.

4.6.2 Mean Absolute Error (MAE)

Mean Absolute Error (MAE) is defined as the average of the absolute errors between the Hausdorff distance of best matching wrinkles of two images and the ground truth (actual wrinkles matching of two images), the mathematical representation of MAE as shown in next equation

$$MAE = \frac{1}{x}\sum_{n=1}^{x}|A_x - B_x| \tag{4.2}$$

. where x is number of images, A_x is best match Hausdorff distance and B_x is ground truth. The researcher used it to evaluate the performance of method which used to investigate the discriminative power of facial wrinkles to be used as soft biometric.

4.7 Summary

In this chapter a general look of the methodology for this thesis is explained. More details about proposed algorithms will discussed in next chapters.

Chapter 5

Automatic Facial Wrinkles Detection Algorithms

5.1 Introduction

This chapter proposes evaluation of automatic facial wrinkles detection algorithms. First, dataset and processing of the dataset images are presented. Second, proposed enhancement algorithm is described. Third, performance assessments of enhancement method and two state-of-the-art (HHF and Gabor Filter) methods are explained. Finally, Result and discussion of experiments in addition to chapter conclusion.

5.2 Modified Hybrid Hessian Filter

Most of existing wrinkles detection method were focused to detect horizontal lines in forehead area, while the wrinkles can appear as vertical lines on forehead and other facial regions. So new method to detect horizontal and vertical wrinkles for all facial regions has been developed. As HHF algorithm Ng et al. (2015*b*) considered outperformed state-of-art-method, so it used as base of developed method to detect vertical lines. The modified Hybrid Hessian Filter was used by Osman et al. (2017) in their study that proposed to investigate the effects of smoking on whole facial wrinkles using social habit face dataset Alarifi et al. (2017*a*).

The original HHF Ng et al. (2015*b*) algorithm detected only horizontal lines, but the facial wrinkles can appear as vertical lines in some facial regions, and some of these regions can effected mainly by smoking Model (1985). So the HHF was modified to detect the vertical lines in addition to horizontal lines. Given a 2D face image I(x,y), it is converted into grey-scale. The directional gradient (*Gx*, *Gy*) is computed from the grey-scale image as represented in equation 5.1:

$$\Delta I(x,y) = (\frac{\partial I}{\partial x}, \frac{\partial I}{\partial y}) \tag{5.1}$$

where $\frac{\partial I}{\partial x}$ and $\frac{\partial I}{\partial y}$ are the directional gradients. *Gx* is $\frac{\partial I}{\partial x}$ and *Gy* is $\frac{\partial I}{\partial y}$.

The *Gy* has been used as the input images for HHF as the input to calculate Hessian matrix H due to it emphasizes the horizontal line. To calculate the Hessian matrix H for vertical line, *Gx* is used for our modified HHF as input. The Hessian matrix *H* is defined as in equation 5.2 bellow

$$H(x,y,\sigma) = \begin{vmatrix} \frac{\partial^2 I(x,y)}{\partial I(y)\partial I(y)} & \frac{\partial^2 I(x,y)}{\partial I(x)\partial I(y)} \\ \frac{\partial^2 I(x,y)}{\partial I(x)\partial I(y)} & \frac{\partial^2 I(x,y)}{\partial I(x)\partial I(x)} \end{vmatrix} = \begin{vmatrix} H_a H_b \\ H_b H_c \end{vmatrix} \tag{5.2}$$

where H_a, H_b and H_c are the outputs of second derivative. The remaining steps to detect the wrinkles are as described in Ng et al. (2015*b*).

5.2.1 Experiments using Social Habits Dataset

In this experiments the effects of smoking on facial wrinkling using computerized algorithm has been investigated. 10 images were selected from Social habits dataset Alarifi et al. (2017*b*), (5 smoker and 5 non-smoker) subjects. The result showed that the smoking is affected on facial wrinkling as shown in figure below.

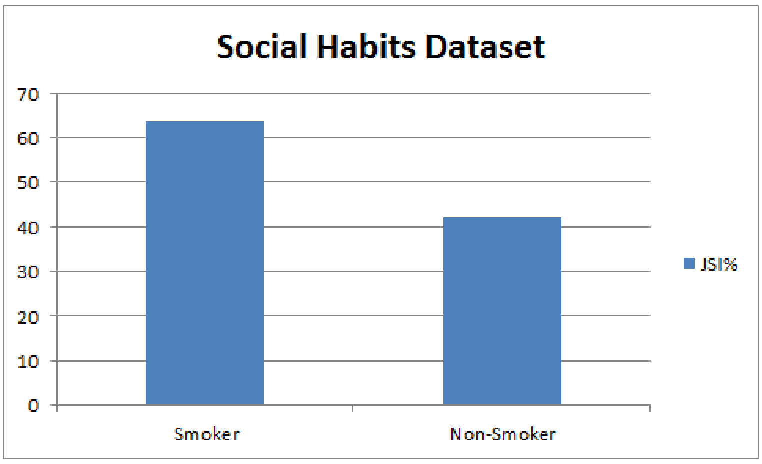

Figure 5.1: A Comparison between the wrinkle detection results on smoker and non-smoker subjects using Social habits dataset

5.2.2 Experiments using Sudanese Dataset

In this step the effects of smoking in facial wrinkling has been investigated using new type of facial skin (Sudanese skin), 10 images from Sudanese dataset have been used in this experiments (5 smoker and 5 non-smoker) subjects. The result showed that the smoking status is affected on facial skin when compared between two group using JSI Jaccard (1901) as shown in Figure bellow.

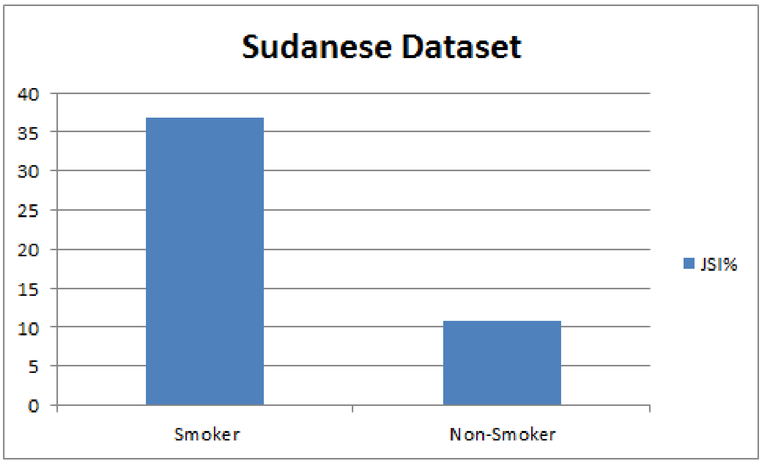

Figure 5.2: A Comparison between the wrinkle detection results on smoker and non-smoker subjects using Sudanese dataset

5.3 Enhancement Method of Automatic Wrinkles Detection

Facial wrinkles considered as an important facial feature that presents on aging faces. Accurate wrinkles detection is corner stone in several image-based applications Choi, Lee, Lee, Park & Kim (2011) Ramanathan & Chellappa (2008). Many wrinkles detection methods were proposed, some of them reported good results like Ng et al. (2015*b*) Ng et al. (2015*b*). In this work, we propose to use the method proposed by Jerman et al. Jerman et al. (2016) for 2D image wrinkles detection (Henceforth, enhancement method). Originally, this method was used to detect vessels Jerman et al. (2016). The method used second order intensity derivative or Hessian for all image's points, in addition to Gaussian scale space of the image. For details of the method, please refer to Jerman et al. Jerman et al. (2016). To illustrate our adoption of the method for wrinkles detection, summarisation of the method as follow. Let denote the intensity of image at coordinate x by $I(x)$; so the Hessian matrix of $I(x)$ at scale s can be represented as in equation 5.3:

$$H_{i,j} = s^2 I(x) * G(x,s) \tag{5.3}$$

for $i, j = 1, ..., D$, where, $x = [x_1, \ldots, x_D]^T$, and $G(x,s)$ is Gaussian method, which is calculated by:

$$G(x,s) = (2\pi s^2)^{\frac{-D}{2}} exp(\frac{-x^T x}{2s^2}) \tag{5.4}$$

To determine the wrinkle's shape and direction; eigenvalues(λ_1, λ_2) of Hessian matrix have been used. According to Jerman et al. (2016) the relation between two eigenvalues can be representing as in equation 5.5:

$$|\lambda_2| \gg |\lambda_1| \tag{5.5}$$

The sign of eigenvalues indicating a bright (dark) structure on dark (bright) background, so it can be represented as in equation 5.6:

$$\lambda_i := \begin{cases} -\lambda_i : bright structure on dark background \\ \lambda_i : dark structure on bright background \end{cases} \tag{5.6}$$

While vessel detection process is based on the brightness/darkness of vessels structure compared to their background, and both of wrinkle detection and vessel enhancement present similar line; so, the same concept will be borrow to detect facial wrinkles. Jerman's et al. Jerman et al. (2016) enhancement method used to detect vessel in 2D and 3D images, their method detected all types of vessels structure (elongated, rounded, and elliptic structures), which is not found in other vessel's detection methods. So, Jerman et al.'s method Jerman et al. (2016) is used to investigate how it will perform on facial wrinkles detection.

The measures of structural isotropy and anisotropy of diffusion tensors (ratio of eigenvalues) which were used by Peeters et al. Peeters et al. (2009) can be applied to Hessian matrices as proposed by Jerman et al. Jerman et al. (2016), this can be illustrated in equation 5.7 bellow

$$V = |\lambda_1 \lambda_2 \lambda_3| \left[\frac{3}{|\lambda_1| + |\lambda_2| + |\lambda_3|} \right]^3 \tag{5.7}$$

Function V can be enhanced to indicate elongated structures; the equation is modified by substituting λ_1 by $(\lambda_2 - \lambda_1)$

$$V = |(\lambda_2 - \lambda_1)\lambda_2 \lambda_3| \left[\frac{3}{|2\lambda_2 - \lambda_1| + |\lambda_3|} \right]^3 \tag{5.8}$$

The output from function V in equation 6 has bad response for low magnitude of λ_3 and λ_2, which was overcome by the calculation of λ_3 at each scale of s. Since our enhancement method is detecting facial wrinkles in 2D image, and according to Jerman et al. Jerman et al. (2016), λ_3 has been substituted by λ_2 to regularize equation 6 to fit 2D images, so λ_2 is calculated at each scale of s as in equation 5.9.

$$\lambda_p(s) = \begin{cases} \lambda_2 & : if \lambda_2 \geq T max_x \lambda_2(x,s) \\ \lambda_2 \geq T max_x \lambda_2(x,s) & : if 0 \leq \lambda_2 \leq T max_x \lambda_2(x,s) \\ 0 & : otherwise, \end{cases} \tag{5.9}$$

Using the output from equation 5.9; Function V is modified as represents in equation 5.10 below:

$$V = \lambda_2^2 \lambda_p \left[\frac{3}{2\lambda_2 + \lambda_p} \right]^3 \tag{5.10}$$

In this equation λ_1 has been eliminated to insure normalized function response as mentioned in Jerman et al. (2016)

After that, an area threshold applied to each image to extract the region of interest (connected pixels), which represents the wrinkles. In this work, the value of scale s is equals to 0.5, 1, 1.5, 2, 2.5, and $tau(t)$ between 0.5 and 1.

5.3.1 Performance Assessment

To evaluate the performance of enhancement method Jaccard Similarity Index (JSI) or Jaccard similarity coefficient has been used. Originally it introduced by Paul Jaccard Jaccard (1901). Ng et al. Ng et al. (2015*b*) Ng et al. (2015*a*) used JSI to evaluate the performance of their wrinkles detection methods. The JSI is calculated by the intersection of A and B divided by union of A and B.

$$JSI(A,B) = \frac{|A \cap B|}{|A \cup B|} \tag{5.11}$$

where A and B are the two compared images (manual annotated wrinkles and method detected wrinkles).

The result of experiments that have been achieved using JSI measure will be explained into next subsections.

5.3.2 Summarise of algorithm steps

1. Data collection

2. Pre-processing of data

3. Calculate Hessian matrix and Gaussian method for image

4. Calculate eigenvalues from Hessian matrix

5. Determine all wrinkle's structures

6. Calculate the output of detected wrinkles as white structure on dark background

7. Apply threshold step to remove the noise from detected wrinkles

8. Evalaute the performance of method output compared to ground truth using JSI

5.3.3 Experiments using FERET dataset

In order to evaluate the performance of the enhancement method, it compared with two state-of-the-art methods; HHF Ng et al. (2015*b*) and Gabor Filter Batool & Chellappa (2015) by reproduce these methods based on the codes we have obtained from the author of algorithms. 45 selected images from FERET Phillips et al. (1998*a*) are used to test the three methods.

More experiments conducted to show how the enhancement method will perform in detecting the wrinkles in ten facial regions individually. The result for all experiments explained in result and discussion section.

5.3.4 Experiments using Sudanese dataset

To test the robustness of the enhancement method in detecting facial wrinkles, further experiments were conducted using 25 selected images from Sudanese dataset. The experiments were based on the state-of-the-art methods, HHF Ng et al. (2015*b*) and Gabor Filter Batool & Chellappa (2015) in addition to enhancement method. The results showed that the wrinkles detection were poor for all methods. When repeated the state-of-the-art methods using the default parameters. For the enhancement method, empirical study have been conducted for $t = 0.5, 0.6, \ldots, 1.0$, the best result was achieved at $t = 1$. More details in result and discussion section.

5.4 Result and Discussion

Unlike previous wrinkles detection methods, which are focused to detect forehead horizontal wrinkles like Ng et al. (2015*b*), Batool & Chellappa (2015), Ng et al.

(2015*b*), the performance of enhancement method has been evaluated on whole face on 45 images selected from FERET dataset Phillips et al. (1998*a*) and 25 images selected from Sudanese dataset. Each selected image was annotated by researcher using hand-labeling, the output annotated images were used as ground truth to evaluate the performance of enhancement method in detecting facial wrinkles.

Figure 5.3 presents the result of experiments . As illustrated in the figure, the enhancement method is performed better than HHF Ng et al. (2015*b*) and Gabor Filter Batool & Chellappa (2015) to detect facial wrinkles with average JSI of 56.17% for enhancement method, 31.69%, 15.87% for HHF and Gabor Filter respectively.

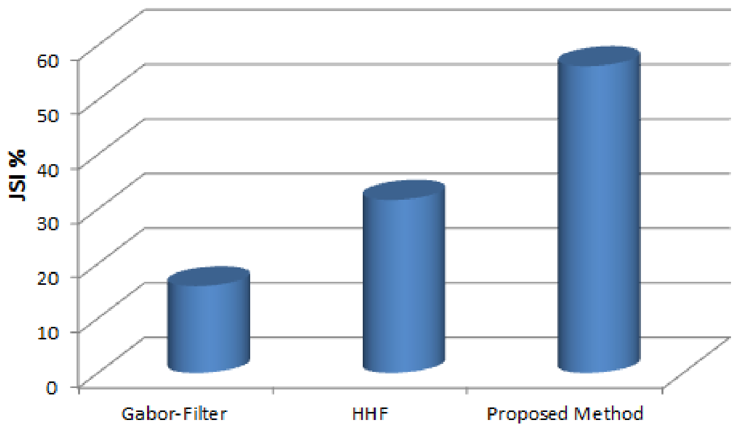

Figure 5.3: JSI of automatic wrinkles detection

More experiments for enhancement method were conducted, the experiments were used to test the detection of wrinkles for each facial ten regions individually. The result explained in Figure 5.4. As shown in the figure, the enhancement method performed better in forehead and eyebag areas, while the detection rate in area of uppereye and upperlid is very low.

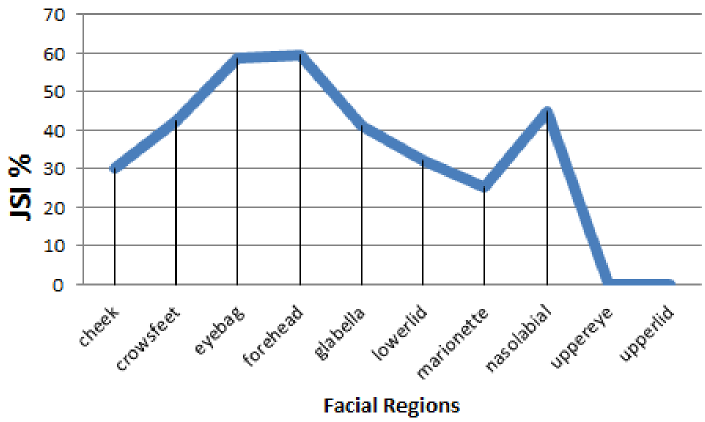

Figure 5.4: JSI of automatic wrinkles detection for ten facial regions

Although this experiment showed that enhancement method is performed better than HHF and Gabor filter in detecting all facial wrinkles, especially vertical wrinkles with average JSI of 56.17% for proposed method, 31.69%, 15.87% for HHF and Gabor Filter respectively, more effort is need to improve the enhancement algorithm to detect facial wrinkles. The method had some drawbacks; it has a problem with illumination (it generates false positive under different illumination settings), in addition to false detection of hair like mustache and cheek.

Figure 5.5 visually compares the result of three methods on an example of FERET image Phillips et al. (1998*a*).

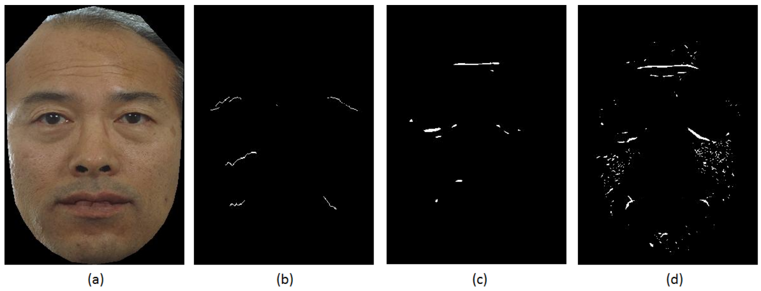

Figure 5.5: A Comparison between the wrinkle detection results of three methods: (**a**) Original image; (**b**) Gabor Filter; (**c**) HHF; and (**d**) Proposed method

Figure 5.4 shows the output from the experiments according to age group. The figure shows the enhancement method is outperformed in detecting facial wrinkles of mid-age and older ages, while HHF has better results in detecting wrinkles of younger age group.

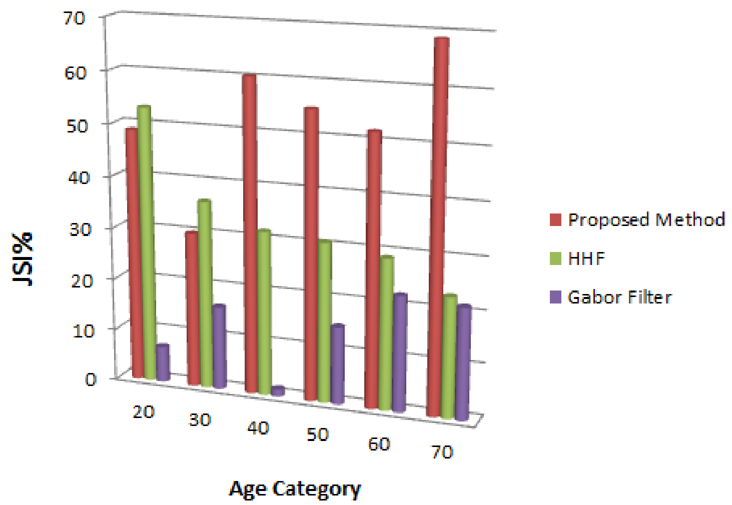

Figure 5.6: A Comparison of the performance of wrinkle detection algorithms on different age group based on FERET dataset

Furthermore, the experiments using 25 images selected from Sudanese dataset was executed. In this study, we tried to examine the wrinkles detection methods on different skin type (mostly brown to dark skin). As explained above the result was poor for all methods with average JSI of 27.26%, 9.43%, and 17.6% for HHF, Gabor Filter, and enhancement method respectively. Although, the overall result is poor, but HHF showed better result on detecting wrinkles for Sudanese dataset. The bad result can be referred to the nature of images, the images were not take under control environment, it were taken under natural light and in different places, the sun light is appear on some of participants images, these factors effects on the result especially enhancement method, because it has a problem with illumination in addition to hair that appear on the face.

As mentioned before in Figure 5.4 that the result of detecting wrinkles in young human faces is better when HHF method Ng et al. (2015*b*) is used; so, the HHF method has shown better result to detect wrinkles in Sudanese dataset than the enhancement method; the reason behind that refers to most Sudanese dataset participant's ages is between 20 and 40 years old.

For the enhancement method, empirical study has been conducted for $t = 0.5, 0.6, \ldots, 1.0$, the best result was achieved at $t = 1$ with average JSI of 20%.

Figure 5.5 shows the output from the experiments according to age group for Sudanese dataset. As explained before, the Figure shows that the enhancement method is better in detecting older ages while HHF is better in young and medium ages.

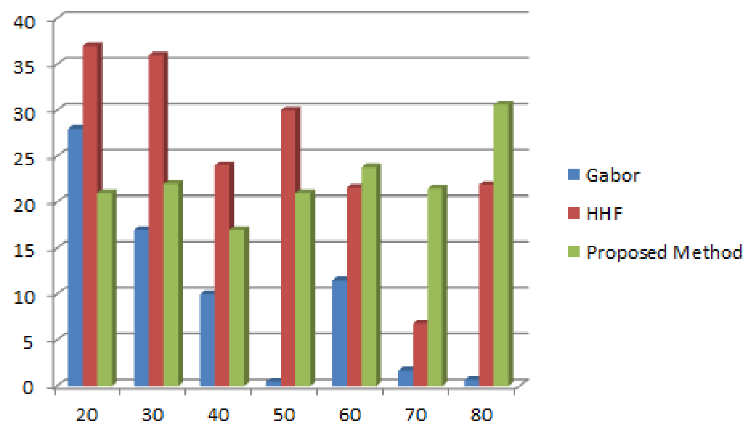

Figure 5.7: A Comparison of the performance of wrinkle detection algorithms on different age group based on Sudanese dataset

5.5 Summary

Existing wrinkles detection methods were focusing on detecting the forehead wrinkles Ng et al. (2015*b*) Batool & Chellappa (2015), however, the wrinkles are important to many applications like age estimation and soft biometric. Many methods are focusing just on detecting the horizontal lines, while it is important to consider the vertical lines in some facial regions. So, it is better to detect wrinkles (vertical and horizontal) for all face rather than just forehead wrinkles. This chapter proposed to use an enhancement method Jerman et al. (2016) to detect wrinkles in 2D images using second order derivatives and Gaussian scale space of image. We had evaluated the performance of the enhancement method to state-of-the-art methods, i.e. HHF Ng et al. (2015*b*) and Gabor Filter Batool & Chellappa

(2015). The experiments showed that; the enhancement method performs better than other state-of-the-art methods with an average JSI of 56.17%. Also the performance of enhancement method to detect facial wrinkles on individual ten facial regions have been evaluated, the experiments showed that the enhancement method perform better to detect wrinkles in the area of forehead and eyebag, while it gives very low detection rate in uppereye and upperlid areas. Moreover, some experiments were conducted to assess the enhancement method, HHF, and Gabor Filter using selected images from new Sudanese dataset, the result was poor for all methods. Overall, the enhancement method performed better than other state-of-the-art methods in detecting facial wrinkles on a subset of FERET dataset, but future work is needed to improve the algorithm, especially in false wrinkles detection for hair and illumination. The output from this method will be used to evaluate our method which is used to investigate the discriminative power of facial wrinkles as soft biometric as will be explained in next chapter.

Chapter 6

Assessment of Facial Wrinkles Uniqueness

6.1 Introduction

This chapter proposes a new method to investigate the uniqueness of facial wrinkles. Section 2, is general overview, section 3, discussed Modified Hausdorff Distance. Experiments , results and discussion are explained in section 4 and 5. Section 5 is the chapter summary.

6.2 Overview

Due to the importance of facial recognition in several applications, the researchers trying to contribute in these fields by using other facial features besides primary features like (eye, mouth, and nose) so as to increase the performance of facial recognition applications. Jain and Park in Jain & Park (2009), they used some of facial marks like facial freckles, moles and scars to improve the facial recognition and retrieval performance. Moreover, Klare et al. Klare et al. (2011) used manually annotated facial marks in addition to primary facial features to distinguish between identical twins. Furthermore, Batool and Chellappa Batool et al. (2013), investigated the discriminative power of facial wrinkles as soft biometric, but their study is focus on forehead area rather than other facial regions. This research would like to investigate the uniqueness of facial wrinkles by focusing on entire facial wrinkles. In this chapter a novel method which assess if te facial wrinkles unique is proposed. According to Dubuission and Jain Dubuisson & Jain (1994), Modified Hausdorff Distance (MHD) considered as a best metric used to decide similarity between two objects, the advantages of MHD over other distances are also demonstrated on several edge maps of objects extracted from real images. So, MHD has been proposed to use to investigate the similarity of facial wrinkles for different people and for the same person regardless the ages.

6.3 Modified Hausdorff Distance

Huttenlocher et al. Huttenlocher et al. (1993) proposed new approach to measure the difference between two set of points called Hausdorff distance (HD). They applied this concept in computer vision to compare two images represented by two sets of points. They claimed that this approach had three key advantages: (1) relative insensitivity to small perturbations of images, (2) simplicity and speedy computation, (3) natural allowance for portions of one shape to be compared with another. After that this measure has been widely used by researcher in several type of application like shape recognition Yu & Leung (2006) and object matching Guerra & Pascucci (2005) Dubuisson & Jain (1994) Batool et al. (2013).

Modified Haudorrf Distance (MHD) is a measure derived from original hausdorff distance. It has been widely used as a metric for object recognition based on lines/contours/curves Yu & Leung (2006) Guerra & Pascucci (2005) Rucklidge (1997) Yi & Camps (1999). As explained in Dubuisson & Jain (1994), MHD is a best distance measurement that can be applied to match two objects, especially, objects matching based on their edge points. MHD has two desirable properties: 1) its value increase monotonically as the amount of difference between the two sets of edge points increases, and 2) it is robust to outlier points that might result for segmentation errors.

As explained by Dubuisson & Jain (1994), MHD is considered as best distance metric for object matching, this is why it used for facial wrinkles matching. MHD computes the distance between two points in two binary images as follow: Modified Hausdorff Distance d_{MHD}: Given two binary images $I(x,y)$ and $J(x,y)$, let $S_I = (x,y); I(x,y) = 1$ and $S_J = (x,y); J(x,y) = 1$. Then the modified hausdorff distance $d_{MHD}(I,J)$ between the two images is given as:

$$d_{MHD}(I,J) = max(d_D(S_I,S_J), d_D(S_J,S_I)) \tag{6.1}$$

where the directed distance $d_D(A,B)$ is given as follows.

$$d_D(A,B) = \frac{1}{|A|} \sum_{a \in A} min_{b \in B} d_E(a,b) \tag{6.2}$$

where A,B are the two images. And a,b are the point from each image.

6.3.1 Summarise of algorithm steps

1. Data collection

2. Pre-processing of data

3. Apply wrinkles detection algorithm

4. Determine wrinkle's similarities using MHD

5. Calculate the output of algorithm

6. Evalaute the performance of method output compared to ground truth using MAE

6.4 Experiments

Facial recognition applications have been improved using a new type of facial features called facial micro features or soft biometric such as: scars, moles Jain & Park (2009) Klare et al. (2011). The facial wrinkles detection algorithms became more robust, precise and showed very good results Ng et al. (2015*a*) Ng et al. (2015*b*), these what motivate us to find an answer to the question: "are facial wrinkles unique?". There is only one study used facial wrinkles as soft biometric and prove that facial wrinkles is unique, but this study was investigate the disriminative power of facial wrinkles as soft biometric in the forehead area rather than other facial regions Batool et al. (2013). In this research, facial wrinkles for entire face have been to answer our question, selected images from FERET Phillips et al. (1998*a*) and Sudanese dataset were used to test our proposed method. Modified Hausdorff Distance (MHD) Huttenlocher et al. (1993) used as base of our method.

The experiments consist of two phases: first experiment based on facial wrinkles that was manually annotated by researcher, while the second one based on wrinkles that detected automatically using our proposed algorithm or enhancement wrinkle detection method which has been explained in chapter 5).

6.4.1 Experiments on Manually Annotated Wrinkles

Several experiments were conducted to investigate the uniqueness of facial wrinkles. Wrinkles' matching was calculated using MHD Huttenlocher et al. (1993). The experiments were executed in several stages: 1) First stage, wrinkles' matching calculated using 24 different subjects images selected from FERET Phillips et al. (1998*a*). 2) Second stage, wrinkles matching calculated using 28 different subject selected from FERET Phillips et al. (1998*a*) and Sudanese dataset, 14 images for each dataset. 3) Third stage, wrinkles' matching was calculated for 5 subjects, 2 images with different age have been for each one of them, the images selected from FERET dataset Phillips et al. (1998*a*).

Wrinkle by wrinkle matching was performed for all images in the stages by calculating the distance between each pair of wrinkles using MHD Huttenlocher et al. (1993).

Moreover, an experiment has been conducted to test how the proposed method is performed when compare between different subject from Sudanese and FERET datasets with the same age.

6.4.2 Experiments on Automatically Detected Wrinkles

To test the robustness of our method in automatically detected wrinkles, further experiments were conducted. Our proposed enhancement method which was explained in chapter 5 have been used to detect selected images from FERET dataset Phillips et al. (1998*a*). As showed in chapter 5, the detection rate of the enhancement function is better compared to other state-of-the-art methods Batool & Chellappa (2015) Ng et al. (2015*b*), we aimed to investigate if the wrinkle patterns recovered with this detection rate had enough discriminative power. Here same experiments are repeated that used in manually annotated images, firstly, wrinkles by wrinkle matching for 10 different subject from FERET Phillips et al. (1998*a*) were conducted. Then, 10 images for 5 subject (two images/subject) from FERET used to investigate the wrinkle matching for the same subject. As explained in manually annotated step, wrinkle by wrinkle matching is based on distance calculation between each pair of wrinkles using MHD Huttenlocher et al. (1993).

6.5 Result and Discussion

Unlike the facial wrinkles as soft biometric study that proposed by Batool et al. Batool et al. (2013) which focused on using forehead wrinkles, our study used to investigate the uniqueness of facial wrinkles using entire facial wrinkles. We used our proposed method to conducted experiments for manually annotated wrinkles and automatically detected wrinkles using selected images from FERET Phillips et al. (1998*a*) and our new Sudanese dataset. To evaluate our proposed method, first, ground truth has been constructed by detecting the wrinkles correspondence between each pair of tested images visually (done by researcher). Then, MHD Huttenlocher et al. (1993) used to calculate the distance between wrinkles in each pair of images to find the similarity between them.

24 images for different people selected from FERET dataset, the experiment was conducted for each pair of images (two different people) by applied MHD for manually annotated wrinkles for each one of them, wrinkle by wrinkle. Second step was to compare 14 selected images from Sudanese dataset with 14 selected images from FERET dataset with the same age in both datasets. Last step was to calculate MHD of 2 images for each person of 5 people selected from FERET. The results showed that the proposed method achieved very good result when compared the output from the three previous experiments with MAE of 9.1, 6.3, 0.91 for different compared subjects from FERET, Sudanese compared to FERET subjects (the selected subject with same age from two datasets), and images for same subject selected from FERET respectively. Figure 6.1 represents MAE comparison between them.

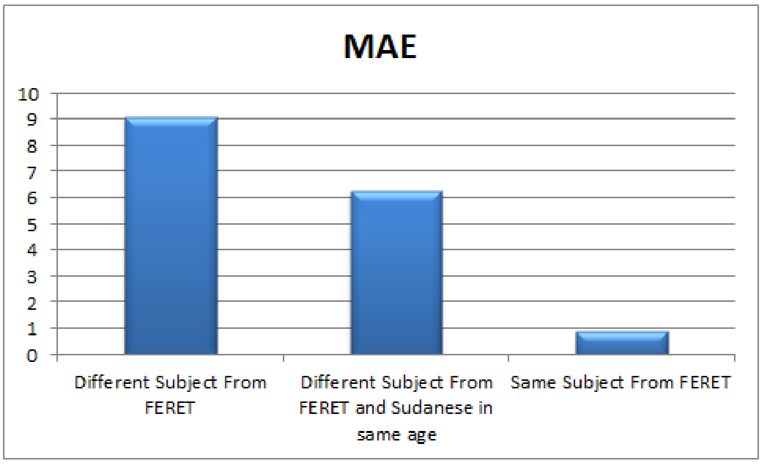

Figure 6.1: MAE comparison for manually annotated wrinkles

Moreover, additional experiments were conducted to test the performance of proposed method in automatically detected wrinkles. In these experiments our enhancement automatic wrinkles detection method was used. This phase is based on 5 different people, 2 different images with differ ages have been used for each one of the five people, images were selected from FERET dataset. The result showed that the proposed method can perform very good for automatically detected wrinkles with MAE of 4.0 when compared different people and 0.4 when compared different images for the same person. Figure 6.2 represents MAE comparison between them.

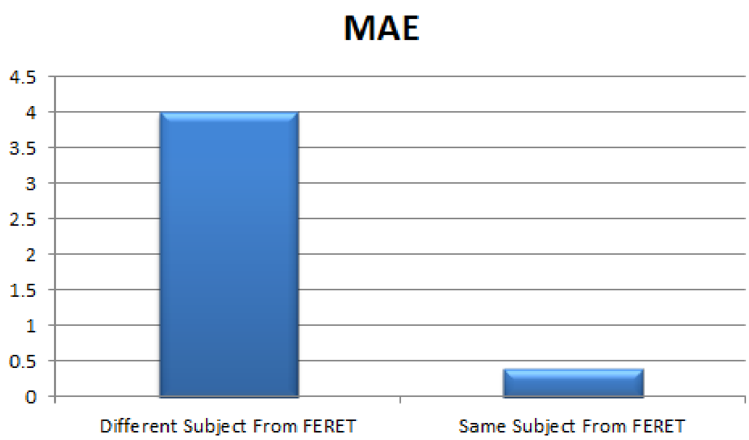

Figure 6.2: MAE comparison for automatically detected wrinkles

6.6 Summary

In this chapter the uniqueness of facial wrinkles has been investigated. MHD is used to determine the wrinkles similarity. several experiments were conducted based on different criteria. The proposed method has been tested into two phases: First one is by using manually annotated wrinkles by researcher and executed many experiments using selected images from FERET and Sudanese dataset. Second phase was based on automatically detected wrinkles using our proposed enhancement automatic wrinkle detection method. The experiments showed that the wrinkles are unique based on MAE comparison for manually annotated and automatically detected wrinkles.

Chapter 7

Conclusion and Future Work

7.1 Conclusion

This thesis has presented an efforts aimed to contribute and address some limitation in automatic wrinkles detection algorithm, beside investigation of the facial wrinkles uniqueness. In the very beginning, the researcher had comprehensive review for the wrinkles detection algorithm including state-of-the-art for automatic wrinkles detection methods which were published in last ten years.Then the researcher conducted Further review for soft biometrics, including the applications that used other facial soft biometric features like moles and scars.

This thesis is contributed in the mentioned area of research by: i) new enhancement wrinkles detection method that detect wrinkles in all facial region has been proposed; ii) Evaluated two state-of-the-art automatic wrinkles detection algorithms (HHF and Gabor filter) to detect wrinkles in all face using FERET and Sudanese dataset; iii) New method using MHD was proposed to investigate the facial wrinkles uniqueness using manual and automatic detection of facial wrinkles is proposed; v) New facial dataset (Sudanese dataset) was collected from sudanese participants. The two proposed methods have been tested with different methods, the experimental results showed that the facial wrinkles are unique for each person from another.

7.2 Limitations and Challenges

As explained in this research that our study is based on two main phases: wrinkles detection algorithm and then investigate the facial wrinkles uniqueness, we will address some limitation and challenges for both of them in addition to other factors.

Even though our proposed enhancement wrinkles detection method produced better result compared to other state-of-the-art methods Batool et al. (2013) Ng et al. (2015*b*) when using FERET dataset Phillips et al. (1998*b*), further improvement is required especially in false wrinkles detection for hair and illumination, in addition to some improvements in the threshod phase. When using Sudanese dataset to evaluate three methods (HHF, Gabor filter, and our proposed method), the result was poor for all due to the nature of Sudanese dataset images which was collected under non control environment.

The experiment which used to investigate the facial wrinkles uniqueness showed very good result, but further experiments are needed on different type of dataset. Moreover, several difficulties and challenges faced us during this study execution: one of the experiment tests is manual wrinkle annotation, which takes long execution time. Also the available facial datasets have a resolution problems, this may affects on the detection process.

7.3 Future Work

The limitations of this research points towards to be addressed in future work. Further improvement on the proposed methods will be as a future work that can be pointed as:

a. A good starting point for future work in the wrinkles detection method is to enhance the threshold process to avoid the false wrinkles detection especially the illumination which is detected as facial wrinkles.

b. To use new datasets that have good images resolution like Bosphorus dataset Savran et al. (2012) to evaluate our proposed methods.

c. To improve the annotation phase by using automatic wrinkles annotator, rather than draw wrinkles by hand which may be prone to errors.

d. For soft biometric, use another metric for wrinkle similarity to add additional prove of using facial wrinkles as soft biometric.

e. To conduct more experiments using other state-of-the-art facial datasets.

f. To collect additional Sudanese images in controlled environment especially for old ages.

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Appendix A

Appendix1

A.1 Samples of questionnaire as filled by some participants

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تقييم تجاعيد الوجه بإستخدام خوارزميات الحاسوب

نموذج الموافقه

هذة الدراسه تتطلب التوقيع على نموذج الموافقه قبل البدء في التقاط الصور للمشارك, تخضع هذة الدراسه لقواعد ولوائح جامعة السودان للعلوم والتكنلوجيا بغرض التطوير والمساهمه في البحث العلمي.

1. لقد فهمت الغرض من الدراسه, وتمت الإجابة على جميع اسئلتي بوضوح.
2. مشاركتي في هذة الدراسه تطوعية, واستطيع الانسحاب منها متى ماشئت دون إعطاء اي اسباب حتى انتهاء الدراسه في ديسمبر 2019.
3. اعلم تماماً أن البيانات التي جمعت خلال هذة الدراسه سوف تستخدم بغرض البحث العلمي حتى 10 أعوام قادمه وبالتالي فقد تستخدم في بحوث علمية اخرى, و في المؤتمرات العلميه.
4. أوافق أن جامعة السودان للعلوم والتكنلوجيا قد تستخدم جزء من هذة البيانات في المجلات والمؤتمرات العلمية.
5. البيانات الخاصة بي ستكون بيانات مجهولة المصدر طوال فترة الدراسه(عدم ذكر الاسم أو التفاصيل الشخصيه).
6. اعلم تماماً أن البيانات ستكون مخزنه رقمياً ومحمية بكلمات مرور, وسوف تكون هوية المشاركين في الإستبيان معرفة فقط من خلال رقم مميز لكل مشارك.
7. أعلم تماماً انه سيتم التعامل مع بياناتي من خلال الرقم المميز فقط و الذي سيتم تخزينه رقمياً.

قرأت الاتفاق المبين اعلاه, و انا أوافق على المشاركة في هذة الدراسه.

الإسم: ....

التوقيع: ....

التاريخ: ....

Figure A.1: Form of Acceptance to take image

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تقييم تجاعيد الوجه بإستخدام خوارزميات الحاسوب

الإستبيان

1. ماهو عمرك؟ ....

2. ذكر ☐ أنثى ☐

هذا الجزء خاص ببيانات التدخين

1. هل دخنت سيجاره من قبل ؟ نعم: ☐ لا : ☐

إذا كنت تدخن وأقلعت

2. كم سيجاره كنت تدخن في اليوم؟
   a. 3 – 1
   b. 6 – 4
   c. 10 – 7
   d. 15 – 10
   e. 20 – 16
   f. 25 – 21
3. كم من الزمن كنت تدخن؟
   a. اقل من سنه.
   b. سنه.
   c. إذا كنت تدخن لاكثر من سنه الرجاء ذكر عدد السنوات بالتحديد (............. سنة)
4. هل أنت الآن مدخن؟ نعم: ☐ لا: ☐

إذا كانت الإجابة بنعم:

5. لكم من الزمن انت تدخن ؟
   a. اقل من سنه.

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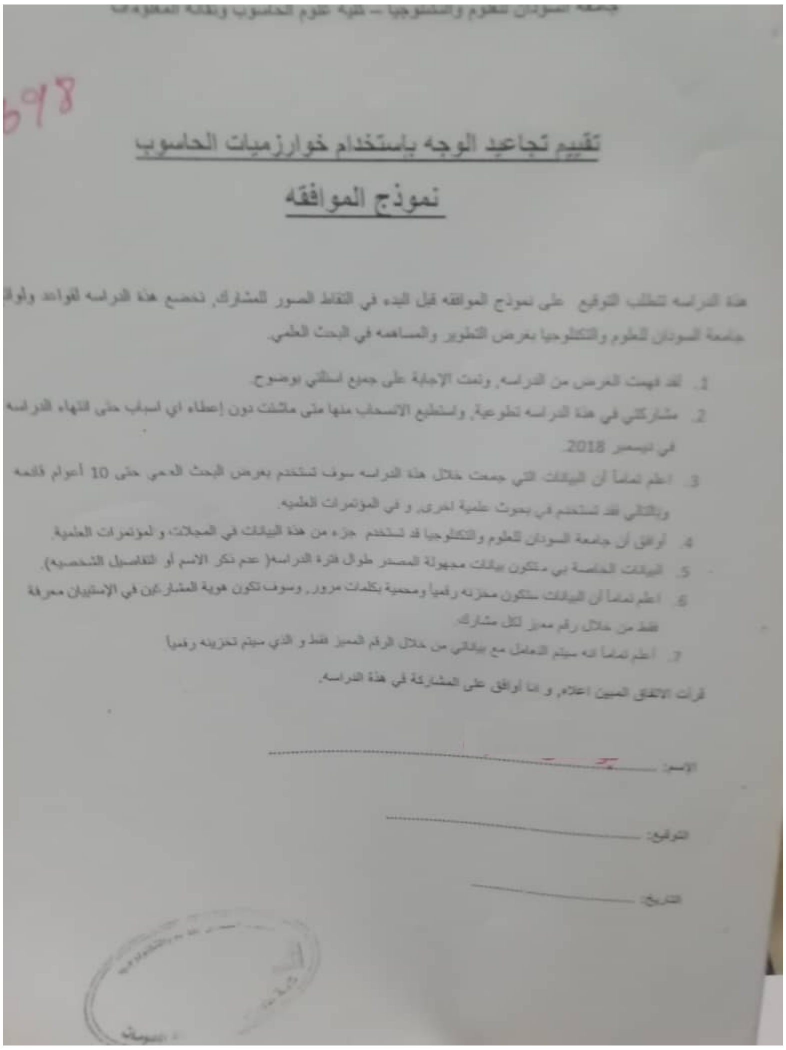
   b. سنه.
   c. إذا كنت تدخن لاكثر من سنه الرجاء ذكر عدد السنوات بالتحديد (............. سنة)
6. كم سيجاره تدخن في اليوم؟
   a. 3 – 1
   b. 6 – 4
   c. 10 – 7
   d. 15 – 10
   e. 20 – 16
   f. 25 – 21
7. إذا لم تكن مدخن, خلال 7 ايام فائته كم شخص دخن بقربك؟
   a. 0
   b. 2 – 1
   c. 4 – 3
   d. 6 – 5
   e. 7+

هذا الجزء خاص بالباحث

رقم المشارك (Participant ID)..................................

Figure A.2: Questionnaire that distributed



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تقييم تجاعيد الوجه باستخدام خوارزميات الحاسوب

نموذج الموافقه

هذة الدراسه تتطلب التوقيع على نموذج الموافقه قبل البدء في التقاط الصور للمشارك, تخضع هذة الدراسه لقواعد ولوائح جامعة السودان للعلوم والتكنلوجيا بغرض التطوير والمساهمه في البحث العلمي.

1. لقد فهمت الغرض من الدراسه, وتمت الإجابة على جميع اسئلتي بوضوح.
2. مشاركتي في هذة الدراسه تطوعية, واستطيع الانسحاب منها متى ماشئت دون إعطاء اي اسباب حتى انتهاء الدراسه في ديسمبر 2018.
3. اعلم تماماً أن البيانات التي جمعت خلال هذة الدراسه سوف تستخدم بغرض البحث العلمي حتى 10 أعوام قادمه وبالتالي قد تستخدم في بحوث علمية اخرى, و في المؤتمرات العلميه.
4. أوافق أن جامعة السودان للعلوم والتكنلوجيا قد تستخدم جزء من هذة البيانات في المجلات، و لمؤتمرات العلمية.
5. البيانات الخاصة بي ستكون بيانات مجهولة المصدر طوال فترة الدراسه(عدم ذكر الاسم أو التفاصيل الشخصيه).
6. اعلم تماما أن البيانات ستكون مخزنه رقميا ومحمية بكلمات مرور, وسوف تكون هوية المشاركين في الإستبيان معرفة فقط من خلال رقم مميز لكل مشارك.
7. اعلم تماما انه سيتم التعامل مع بياناتي من خلال الرقم المميز فقط و الذي سيتم تخزينه رقمياً

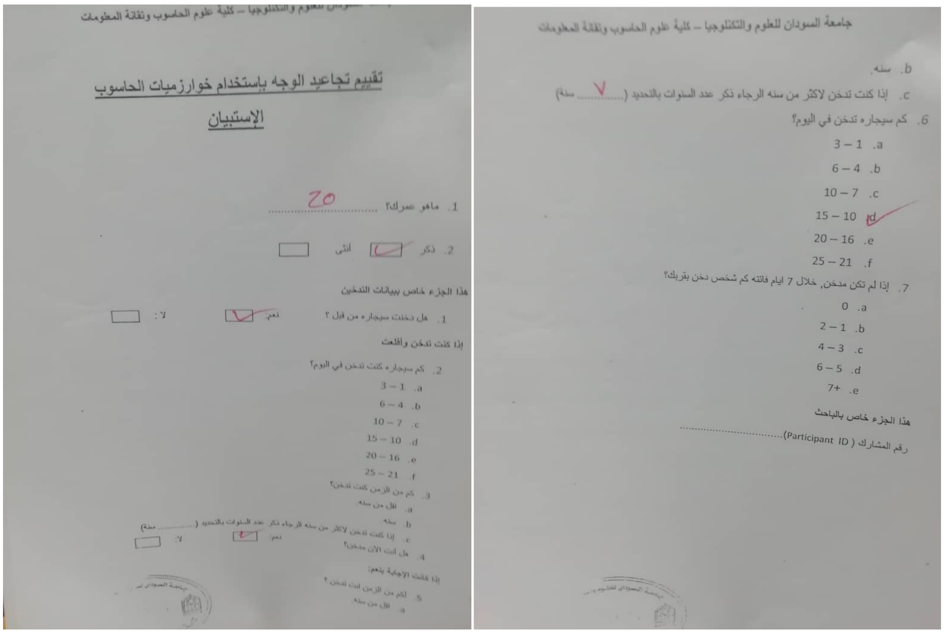
قرأت الاتفاق المبين اعلاه, و انا أوافق على المشاركة في هذة الدراسه.

الإسم: ....

التوقيع: ....

التاريخ: ....

Figure A.3: Sample of filled acceptance form by one participants



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تقييم تجاعيد الوجه باستخدام خوارزميات الحاسوب

الإستبيان

1. ماهو عمرك؟ ......20......

2. ذكر ☑ أنثى ☐

هذا الجزء خاص ببيانات التدخين

1. هل دخنت سيجاره من قبل ؟ نعم: ☑ لا: ☐

إذا كنت تدخن وأقلعت

2. كم سيجاره كنت تدخن في اليوم؟
   a. 3 – 1
   b. 6 – 4
   c. 10 – 7
   d. 15 – 10
   e. 20 – 16
   f. 25 – 21
3. كم من الزمن كنت تدخن؟
   a. اقل من سنه.
   b. سنه.
   c. إذا كنت تدخن لاكثر من سنه الرجاء ذكر عدد السنوات بالتحديد (............ سنة)
4. هل انت الآن مدخن؟ نعم: ☑ لا: ☐

إذا كانت الإجابة بنعم:

5. كم من الزمن انت تدخن ؟
   a. اقل من سنه.

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   b. سنه.
   c. إذا كنت تدخن لاكثر من سنه الرجاء ذكر عدد السنوات بالتحديد (....٧.... سنة)
6. كم سيجاره تدخن في اليوم؟
   a. 3 – 1
   b. 6 – 4
   c. 10 – 7
   d. 15 – 10 ✓
   e. 20 – 16
   f. 25 – 21
7. إذا لم تكن مدخن, خلال 7 ايام فائته كم شخص دخن بقربك؟
   a. 0
   b. 2 – 1
   c. 4 – 3
   d. 6 – 5
   e. 7+

هذا الجزء خاص بالباحث

رقم المشارك (Participant ID).......................

Figure A.4: Sample of filled Questionnaire

Appendix B

Preliminary Experiments

B.1 Local Binary Pattern (LBP)

LBP is originally developed by Ojala et al. Ojala et al. (1996), it is a method for texture analysis. The basic idea for this method is to extract the local features in an image by using pixels neighborhood and comparing between them, take pixel as center then using threshold between the center and neighbors, then compare if the intensity of the center is greater than or equal its neighbor represent it with 1 or if it is less than represent it with 0. The result from previous step will be a binary number for each pixel, just like 11110011. This binary number called local binary patterns or LBP codes Shan et al. (2009). The equation bellow represents the lbp method mathematically.

$$LBP_{R,P} = \sum_{i=1}^{p-1} (g_i, g_c) \times 2^i \tag{B.1}$$

where, R: radius of the circle from which the surrounding pixels are taken, and P: number of surrounding pixels.
LBP operator used a fixed 3x3 neighborhood as shown in figure 4.1 bellow.

The original LBP method fixed to 3×3 this made the method failed in the cases when the size is more than 3×3, so extended LBP proposed to solve this problem to make it appropriate to any size as shown in figure 4.2.

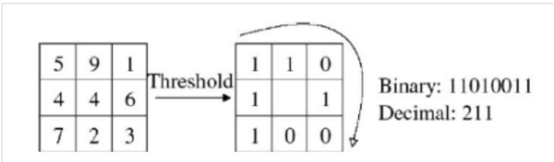

Figure B.1: The basic LBP operatorShan et al. (2009)

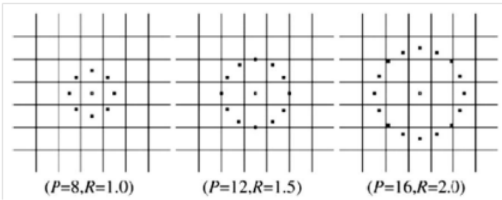

Figure B.2: Three examples of extended LBP Shan et al. (2009)

B.1.1 Uniform pattern

When the binary string in the local binary pattern is considered as circular and this binary string contains at most two bitwise transitions from 0 to 1 or from 1 to 0 for example: 00000000, 001110000 and 11100001, it is called uniform patterns.

B.1.2 Non uniform pattern

If the patterns contains four or six transition like 11001001 (4 transitions) and 01010011 (6 transitions) it is called non uniform. As shows in figure 4.3, the example results with white or black representation of the pixels which the intensity of it are less or more than the central pixel. When surrounding pixels are all black or all white then that image region is called flat or featureless. While groups of continuous white or black pixels appear together this is can be considered "uniform" patterns and it can be interpreted as corners or edges as shown in the figure 4.3. But if the pixels switch between black and white, the pattern is considered as "non-uniform" pattern Ojala et al. (1996).

B.2 Sequential Minimal Optimization (SMO)

As explained by Platt et al. Platt et al. (1999) Sequential Minimal Optimization (SMO) is one of the support vector machine (SVM) training functions , originally

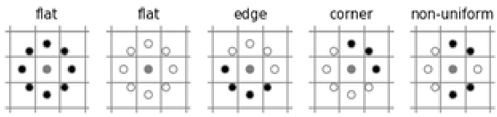

Figure B.3: Represent uniform and non uniform pattern Shan et al. (2009)

proposed to solve the problem of a very large quadratic programming (QP) optimization problem in training SVM. SMO solved the QP optimization problem by decompose the large problem into series of smallest possible QP problems, and solve this small problems analytically, which avoid the time consuming, another advantage that SMO does not need extra large storage area; very large SVM training problems can be store inside the memory of personal computer.

Unlike other SVM methods, SMO chooses to solve the smallest possible optimization problem at every step. This possible optimization problem involves two Lagrange multipliers Rockafellar (1993). At every step SMO chooses two Lagrange multipliers to jointly optimize, finds optimal values for these multipliers and then update the SVM to reflect the new optimal values Platt et al. (1999).

B.3 Experiments using LBP and SMO

Automatic wrinkles detection algorithm has been developed, this algorithm used 150 images randomly selected from FERET dataset Phillips et al. (1998*b*). When these images were selected, many preprocessing steps applied to prepare images to next step. Face alignment applied to all selected images; triangulated mesh is obtained using Delaunay's method Rebay (1993) on the mean shape (the points that image should be aligned according to it), after that mean shape created; these two steps used to wrap image. After that the forehead area cropped manually, figure 4.4 illustrates the cropped forehead images.

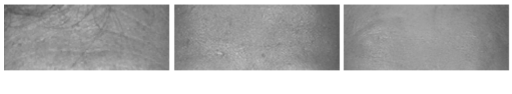

Figure B.4: Cropped Images

To test the performance of wrinkles detection method, 150 cropped images from FERET dataset Phillips et al. (1998*b*) were used. LBP method Ojala et al. (1996) extract the features from the selected images. The patterns that were extracted were used to train and test the model for classification. In classification step SMO Platt et al. (1999) have been used, SMO model used 70% of extracted features data for training and 30% for testing, the recognition rate was 61%.