Facial Makeup Detection Using HSV Color Space and Texture Analysis

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ABSTRACT

Facial Makeup Detection Using HSV Color Space and Texture Analysis

Shiva Varshovi

In recent decades, 2D and 3D face analyses in digital systems have become increasingly important because of their vast applications in security systems or any digital systems that interact with humans. In fact the human face expresses many of the individual’s characteristics such as gender, ethnicity, emotion, age, beauty and health. Makeup is one of the common techniques used by people to alter the appearance of their faces. Analyzing face beauty by computer is essential to aestheticians and computer scientists.

The objective of this research is to detect makeup on images of human faces by image processing and pattern recognition techniques. Detecting changes of face, caused by cosmetics such as eye-shadow, lipstick and liquid foundation, are the targets of this study. Having a proper facial database that consists of the information related to makeup is necessary. Collecting the first facial makeup database was a valuable achievement for this research. This database consists of almost 1290 frontal pictures from 21 individuals before and after makeup. Along with the images, meta data such as ethnicity, country of origin, smoking habits, drinking habits, age, and job is provided. The uniqueness of this database stems from, first being the only database that has images of women both before and after makeup, and second because of having light-source from different angles as well as its meta data collected during the process.

Selecting the best features that lead to the best classification result is a challenging issue, since any variation in the head pose, lighting conditions and face orientation can add complexity to a proper evaluation of whether any makeup has been applied or not. In addition, the similarity of cosmetic’s color to the skin color adds another level of difficulty. In this effort, by choosing the best possible features, related to edge information, color specification and texture characteristics this problem was addressed.

Because hue and saturation and intensity can be studied separately in HSV (Hue, Saturation, and Value) color space, it is selected for this application.

The proposed technique is tested on 120 selected images from our new database. A supervised learning model called SVM (Support Vector Machine) classifier is used and the accuracy obtained is 90.62% for eye-shadow detection, 93.33% for lip-stick and 52.5% for liquid foundation detection respectively. A main highlight of this technique is to specify where makeup has been applied on the face, which can be used to identify the proper makeup style for the individual. This application will be a great improvement in the aesthetic field, through which aestheticians can facilitate their work by identifying the type of makeup appropriate for each person and giving the proper suggestions to the person involved by reducing the number of trials.

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Completing my master's thesis was a unique opportunity in my life that perhaps will never repeat again. However the achievements in these two years will affect definitely my whole life. This acknowledgment is the least possible way I can thank the many people who made this thesis possible.

Foremost, I would like to express my sincere gratitude to my supervisor Prof. Ching Y. Suen for the continuous support of my master's study and research, for his patience, motivation, enthusiasm, and immense knowledge. He supported me to follow my passion in a wonderful university. His guidance helped me in all the time of research and writing of this thesis. I could not have imagined having a better advisor and mentor for my studies.

Special thanks to my committee, for their encouragement, insightful comments, and hard questions.

Besides my supervisor, I would like to thank Mr. Nicola Nobile who was a great help through the long and tedious process of photo shooting, preparing the forms and collecting all the 2700 images from the participants. Without his time and effort gathering this big database was impossible.

DEDICATION

This thesis is dedicated to:

My father, who taught me how to be strong against hardships…

My mother, who taught me how to follow my dreams…

My love, a supportive and loveable man, who always put my wishes ahead of his…

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Chapter 1

1. Introduction

1.1. Preface

2D and 3D human face images have been under intense study in the past these decades, moreover it is a main research area in pattern analysis and computer vision. Human face expresses vast information about the person such as: identity, gender, ethnicity, emotional status, skin color, and age and health state. Retrieving such information is helpful in computer systems and medical software. Related research covers these main topics: analyzing human expression and human attractiveness. Simulating human expression for animation characters, inferring human expression are some of the applications of human face expression analysis. The latter challenging issue has been controversial for many centuries, since there is not a defined rule and measure for beauty. Discovering beauty standards can improve many scientific areas such as: human science, plastic surgery and orthodontics[1].

Aside from the importance of defining beauty, today's modern world demands beauty in digital world. This encourages producers or conversely consumers require producers to create more visually attractive products. We love our Operating System to be fancy with a lot of nice animations, websites are also getting more beautiful with creative styles, and online community websites are another example of products that needs to be attractive to catch the attention of users. This is an unending competition which not only comprises the objects and products but also our own body. Superstars would be ignored if they are not beautiful anymore or if they are not according to beauty standards. Journals, TVs and internets are full of retouched photos of superstars; usually their faces wear heavy makeup but beside that many enhancement techniques would be applied on the photo to improve them, such as smoothing skin, removing acne and spots, lengthening the neck, changing the eye size and so on.

With all these changes to human face in digital images and videos it has become necessary to identify them for security reasons. Criminals apply some extent of makeup to hide their real faces, if computers can distinguish and recognize such changes it would be easier for police to arrest them.

For women it would be so exciting to know whether the type of makeup they have would propel to beauty standards or not. This application would be so helpful for aesthetic specialists in order to facilitate their work. Moreover by identifying the type of makeup, the proper suggestions could be given to the person involved.

The aim of this thesis is to find whether the person has makeup or not and also the locations of makeup. Since there is no public facial makeup database it is essential to create a facial database of women before and after makeup. Collecting a database was the most time consuming part in this research because of the difficulties of finding people eager to participate, moreover the variation of face type and nationalities makes the makeup part a little complicated. After collecting the database, the face landmarks should be detected. This is an important step in face analysis, since any misrecognition of landmarks can deteriorate the result dramatically.

In methodology suitable features and techniques will be introduced in order to use them in the appropriate classifier. There are only two classes for the classifier it is whether zero or one, which means no-makeup and with makeup respectively. In the last chapter of this thesis the results and future works will be discussed.

1.2. Problem Statement

In face analysis area all the researches (although not many) about the makeup on face, focus on applying makeup on face photos. For instance, Brand and Pletscher[2] worked on retouching an image and removing flaws, moles and ance from face. Other related research is to transfer makeup from one image to another image. Tong *et al*, developed Example-Based Cosmetic Transfer that learns how the face changes before and after makeup,[3]. But none of these researches specify whether the facial image has makeup or not. The need for detecting makeup and locating it in order to benefit in many applications was the motivation to do this research.

The main issues that are addressed in this thesis:

1. Detecting makeup on different areas of the face:
   Since the makeup can be applied on different parts of the face, each part of the face such as eyes, lips and skin are studied separately.
2. Lack of facial makeup database:
   It is important to create an appropriate database for any classification technique. In digital makeup detection, this is the first step in this research, because there is no other database or result available to compare with. Although many published facial databases are for public use, none of them is specifically designed for makeup detection purposes. The collected database for this technique consists of

digital photos before and after makeup of 21 women. It is also provided with some meta data about the participants.

3. Detecting landmarks on the new database:
   Most of the public facial databases are provided with landmarks of face. This was also an issue for the new database. The Active Shape Models (ASM) methodology was used to detect the critical points of the face. Finally, it was necessary to validate the landmarks and store them in a CSV file format for future use.

1.3. Applications

Detecting makeup of digital faces has the following applications:

- It helps makeup artists to find the best type of makeup for the person. A main highlight of this technique is to specify where makeup has been applied on the face, which can be used to identify the proper makeup style for the individual. This application will be a great improvement in the aesthetic field, through which aestheticians can facilitate their work by identifying the type of makeup appropriate for each person and giving the proper suggestions to the person involved by reducing the number of trials.

- It can be used for identification in security systems. Criminals apply some extent of makeup to hide their real faces, if computers can distinguish and recognize such changes it would be easier for police to arrest them. This can be used in airports along with their identification system.

Moreover for conducting this research a face database is collected that can be used in other areas of research such as, age estimation, age-makeup relations and effect and race detection.

1.4. Thesis Organization

This thesis is organized as follows:

- Chapter 2 describes the definitions of beauty and the history of applying makeup. It also describes the different parts of the human face and their related definitions. The makeup techniques that are used when creating database, is also explained. Finally, the related computer-based works both in beauty and makeup for digital photos is described.
- Chapter 3 introduces the new collected facial makeup database. It compares the different public facial database available to use as well.
- Chapter 4 discusses the methodology to extract features from the face. Pre-processing and landmark detection is described first and then explains two categories of features, color and texture used for classification.
- Chapter 5 is about the implementation and the results of the three subsystems (eyes, lips and skin). The weaknesses and the strengths of each part are discussed as well.
- Chapter 6 gives the conclusions about the methodology. The future works are the final part of this thesis.

Chapter 2

2. Definitions and Related Works

2.1. Human Face

Human face conveys a great deal of information about the person's emotions, life style and background. For humans, face perception is an autonomous complex process done by the brain, however for machines to be able to process the face and extract information, complicated algorithms are needed. In this section some of the face characteristics will be discussed.

Identity

As of today, it is estimated 7.025 billion people live on earth and surprisingly their face is almost unique, even the twin brothers and sisters are not completely identical.

Nevertheless for many security systems having only identical face is not good enough, at the present time other information are necessary for identification such as iris and finger print. However still face photo is an indispensible part in identification documents such as passport and driving license.

Face identification is an important and challenging topic in machine vision area. It has many applications but the most critical is identifying criminals and terrorists in public places. In 2010 Margarita et al introduced a secure system for computation of face identification. Their approach, by saving the confidentially of both the client and the database of photos, searches the clients' photo among stored photos of available photos. The obtained result reveals that face identification can be efficient even in real-time processing [4].

Age

Aging is a natural and gradual process that never stops. This undesirable process causes different alteration on the human face, Figure 2-1.

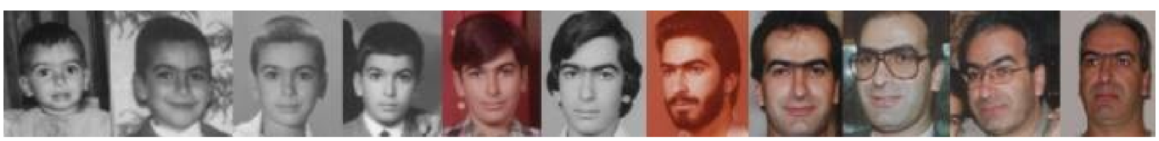

Figure 2-1 Age progression from childhood to adulthood [5]

As it can be seen from the Figure 2-1 human face age-progression has two main changes: from childhood to pre-adulthood and from adulthood to end. Therefore for people with ages ranging from 1 to 25 the following changes could be seen [6]:

- At the age of 1 the head is very rounded, the bridge of the nose is flattened, the eyes look large and rounded and the hair is soft and fine.
- Gradually the cranium expands, the eyes elongate and become less rounded
- The bridge of the nose continues to grow up, its lower cartilages becomes apparent and tip takes shape

- The face continues to elongate as the nose length and the chin length increase
- The pattern of the hair becomes established, it is less fine and the color darkens.
- The forehead becomes less prominent
- The mouth grows to accommodate the permanent teeth
- The squarish form of the chin becomes obvious
- The cheek bones become prominent
- The ears will no longer be oversized
- The teeth do not seem so oversized for the face
- The mandible continues to square and form and looks more masculine and mature

And for people older than 30 the following effect are observed:

- Deepening traverse lines across the forehead
- Deepening glabellar vertical lines
- Formation of nasal lines across the top of the nose
- The jaw lines become less firm
- Formation of neck lines
- Jowls and a double chin may appear
- The tissues under the neck sag
- The ears get larger and wrinkles appear in front of the tragus
- The lips continue to thin (especially in people with thin lips in youth)
- The dental changes may become apparent , increasing lines accordingly

To estimate the age exactly the machine must completely classify the changes in each age although some might appear sooner and some later because of many factors such as race and gender. Usually females of the same race look older than the males.

Figure 2-2 The effect of life style on identical twins[1]

Although aging is a natural process on our body, some habits can expedite and some can delay the process. Figure 2-2 shows the effect of different life style, the person on right averaged a pack and a half of cigarettes every day for sixteen years; she has also been exposed to sunlight very often, however the woman on left never smoked and avoided sunlight. Many parameters are involved in this complicated process such as [6]:

- genetics (Asians, Europeans)
- exposure to sunlight
- smoking
- consumption of alcoholic drinks
- nutrition

Computer scientists are now researching on how to estimate people's age. For this report a survey is done to see how accurate people can guess the age of others. Thirty participants were asked to guess the age of the people in each image. This survey consists

[1] http://www.healthism.com/articles/5-secrets-to-looking-younger

of 25 images (different ages, nationalities, colour and greyscale) from FG-NET database [7]. Some of those images were for one individual at different ages, Figure 2-3.

Figure 2-3 Sample pictures used for age estimation survey from FG-NET database

Table 2-1 and Table 2-2 reveal important information about the human's ability in estimating the age of others only by one photo. The following conclusions are obtained from this survey.

Table 2-1 Comparison of the MAE for Each Survey Participant

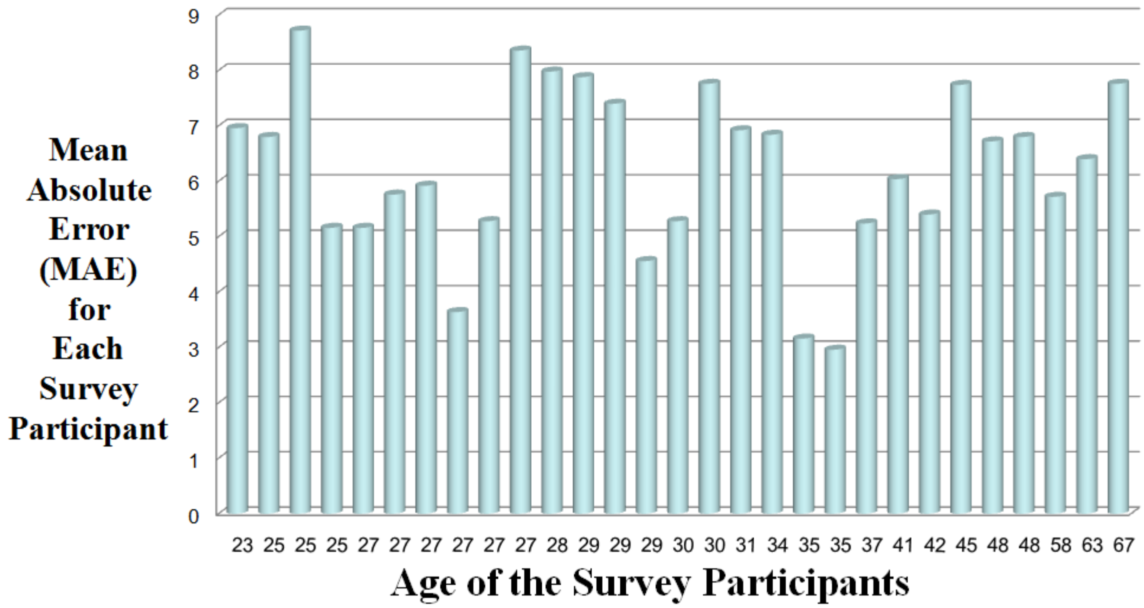

Table 2-2 Error Rate for Each Photo (Error Rate: Difference between Average of Estimated Ages and real age for each image)

- Computers are better than humans at estimating ages and Higher quality images yield better results (fewer errors).
- Older participants did not necessarily give more accurate results

- A 35-year-old male yielded the best result (MAE)
- Error rates differed for color versus gray scale images
- Images of people in age ranging 20-40 and 60+ yielded more errors
- Extra details such as a bride's dress and a baseball cap yielded fewer errors
- Overall MAE was higher than MAE by 4.37 years on FG-NET database

Nationality

Human face reveals much information about the race of the humans. Johann Friedrich Blumenbach, naturalist, physician and anthropologist categorized human races into five categories [8]:

- the Caucasian race or white race
- the Mongolian or yellow race (Asian)
- the Malayan or brown race (Pacific Islander)
- the Negroid race, or black race
- the American or red race

Expression

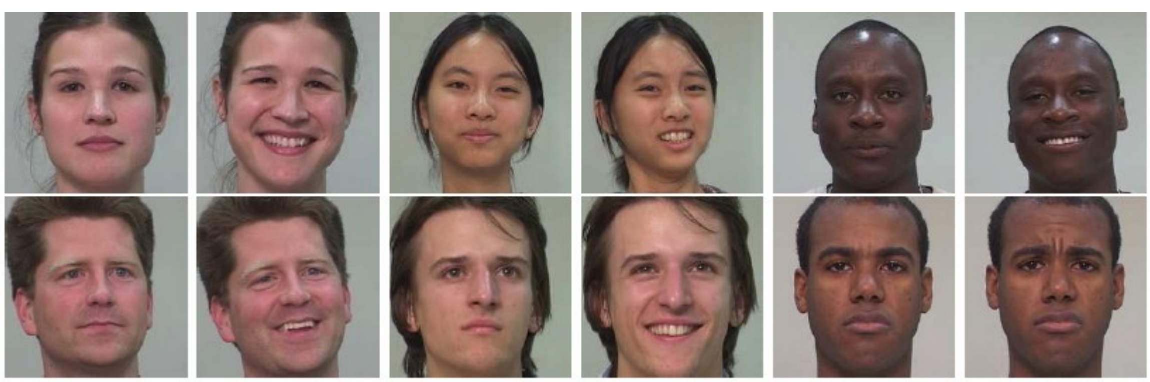

Figure 2-4 Sample images from MIT facial expression

Expressions and emotions play an important role in our daily life, Figure 2-4. Human's social behaviour is strongly affected by perception, interpretation and response to these signals. Peterson and Deffenbacher et al have found that individuals from the same race are more accurate in interpreting the expressions and emotions. Although individuals recognise human's expressions with no delay, reliable human-machine interface that can recognise expressions is still a challenge. Automatic expression recognition can be so beneficial while interacting with humans [9].

Gender

Gender is the behavioural, cultural, or psychological traits typically associated with one sex which can be identified from the facial features such as the width of the eyebrows, skull structure, nose size and so on. Figure 2-5 shows the skull of female and male from frontal and lateral view. Some of the differences of male face with female face are as follows:

- prominent supra-orbital (brow) , ridges (frontal bossing) resulting in deep set appearing eyes
- flatter and narrower eyebrows
- slightly narrower eyes
- eyes less "wide open" (eye lids slightly closed)
- slightly longer and/or wider nose
- slightly thinner lips (especially upper lip)
- square/angled and or larger jaws

Figure 2-5 Skull of male and female

2.2. Beauty

It is nearly impossible to clearly define beauty but it may be defined as *a combination of qualities that give pleasure to the senses or to the mind.* In Oxford dictionary beauty is defined as: "A combination of qualities, such as shape, color, or form, which pleases the aesthetic senses, especially the sight." and the Renaissance artist Leon Battista Alberti defined it as: "The summation of the parts working together in such a way that nothing need to be added, taken away or altered."[10]. The Beauty Myth, Naomi Wolf states that there is no such thing as quality called beauty that objectively and universally exists [11]. However, we cannot deny the obvious universal concern of beauty among Americans according to the existing extremely profitable industries: cosmetics and weight loss or the fact that women earn more in two professions like modeling, indicating the importance of face and body harmony. Lack of this harmony can result in losing self-esteem and isolation from society.

To define attractiveness we have to answer a few questions. Is the perception of beauty culturally independent or it is the cultural convention? The relationship between culture and human behaviour has been studied. As Cosmides, Tooby and Barkow quote: "Culture is not causeless and disembodied. It is generated in rich and intricate ways by information-processing mechanisms situated in human minds. These mechanisms are, in turn, the elaborately sculpted product of the evolutionary process. Therefore, to understand the relationship between biology and culture one must first understand the architecture of our evolved psychology."[12]. Now scientists believe that there is universality for facial movements to express emotion among nations. Likewise there is a consensus among linguists that there is a universal grammar behind all the languages. Similarly, although there are many cultural and ethnical differences in human judgment of beauty, yet there are general geometric features of face that seem pleasing to many people, therefore the hypothesis that beauty is an arbitrary cultural convention may not be true.

However many researchers who are working on human attractiveness have categorized the type of faces that are considered to be more beautiful: neonate features such as a small nose and high forehead, or mature features such as prominent cheekbones, or expressive features such as arched eyebrows [13]. We will discuss more in detail in future sections.

2.2.1. History of beauty

Human beauty is an old topic in many areas such as physiology, neuroscience and biology, but analyzing human beauty via computer is a very new topic in pattern recognition. Beauty is a controversial topic in human science. Is there any canon[1] to define it? Or beauty is in the eye of the beholder? Every year people spend lots of money on enhancing their beauty by either temporary ways such as makeup or permanent ways like surgery and orthodontics. In order to have a prosperous social life they tend to have face and body harmony. According to the publications of *Darwin's Descents of Man, 1878* [14], Standards of beauty are gradually learned by children by exposing to media and culture in which they live and beauty standards are culturally specific.

[1] A canon in the sphere of visual arts and aesthetics, or an aesthetic canon, is a rule for proportions, so as to produce a harmoniously formed figure (definition by Wikipedia).

Many researchers like Bernstein and Mclelian [15], suggest that diverse nations have their own distinct and similar structural features that appear to be attractive despite the racial and cultural background of the viewer. Samuels & Ewy, [16], showed that babies apart from their cultures and ethnicity as young as three/six months can distinguish pictures of adult-judged attractive and unattractive faces. They prefer attractive ones. According to these two significant findings, there must be a universal stimulus dimension of faces that people of every age range cross-culturally view as attractive.

Artists, since the introduction of art, have been trying to apply some rules to have more beautiful paintings or sculptures. They look at beauty as an objective and measurable property. Defining some proportions and rules by Greek sculptor Polycleitus in the early 4^{th} century, was the first mathematical measurement of beauty. He wrote a treatise (kanon) and designed a male nude presenting his aesthetic theories of the mathematical bases of artistic perfection. The roman architect is known for describing the facial trisection (Vitruvius trisection). His ideas were based on the classical Greek sculptors [17]. He defined the concept of symmetry (symmetria). He believed that there is a kind of symmetrical harmony and so it is with perfect building. Vitruvius also defined the proportion of head and face height to standing height, emphasizing that the ideal face can be divided vertically into three distinct facial thirds.

Renaissance artists like Leonardo da Vinci developed further theories and canons of facial proportional relationships after Vitruvius works.

In beauty there is no limitation. With every face there are a lot of challenges to improve beauty with updated techniques. Although use of makeup has a history of over 4000 years, only in last decade we see different and bizarre techniques not only to make people beautiful but also to make them different from others, techniques such as piercing, tattoos, extremely fashioned hairdressing and permanent makeup caused by surgery are examples of our modern world makeup. In fact the norms of beauty canon may vary over time due to evolution of physical decoration techniques.

2.2.2. Mathematical Rules of Beauty

Although the definition of beauty is controversial and it is in the eye of the beholder, for centuries, scientists and artists have tried to discover some beauty rules. In order to quantify beauty, scientists need to come up with a scientific measure of attractiveness. These measurements could be universal; characteristics that are appealing among different nations.

2.2.2.1. Vitruvian Man

"Vitruvian Man" is the world famous drawing of Leonardo da Vinci, 1487, in his treatise *De Architectura*[18], which is accompanied by description of ideal human body proportions with geometry described by the ancient Roman architect *Vitruvius Pollio*. This canon also has some description of ideal human face proportions, Figure 2-6:

- the distance from the bottom of the chin to the nose is one-third of the length of the head
- the distance from the hairline to the eyebrows is one-third of the length of the face
- the length of the ear is one-third of the length of the face

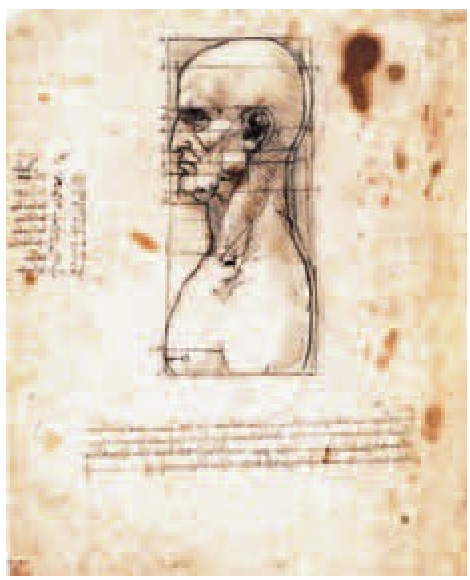

Figure 2-6 Leonardo da Vinci's male head in profile with proportions, c. 1490

meaning that *If we take the height of the face, the distance from the bottom of the chin to the underside of the nostrils is one third of it; the nose from the underside of the nostrils to a line between the eyebrows is the same; from there to the lowest roots of the hair is also a third, comprising the forehead*, Figure 2-7, [19] .

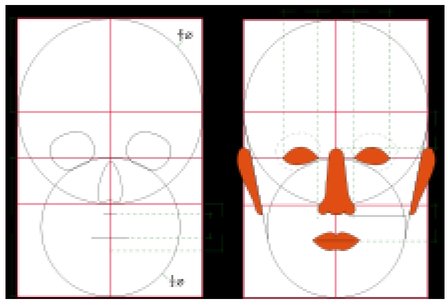

Figure 2-7 Human head proportions

Some scientists believe that being in proportion and symmetry increases the attraction of people both to body and face, moreover they are considered as healthier and more beautiful.

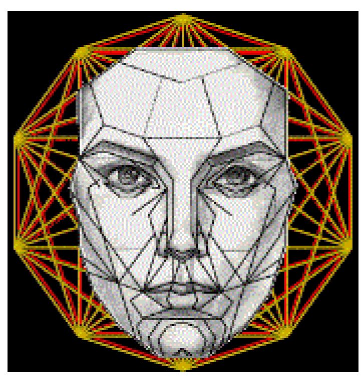

Figure 2-8 Marquardt Beauty Mask

2.2.2.2. Golden Proportions

The Golden ratio, a number in mathematics and science, is based on Fibonacci sequence and is a geometrical proportion widely used for human form. The Golden ratio is an irrational number approximately ϕ = 1.6180339887..., which is obtained by dividing a segment in two parts, a and b such that $a/b = (a+b)/a$. This number is based on Fibonacci Numbers, where every number in the sequence is the sum of the previous numbers. Apart from the face, many proportions in nature are compliant with the golden ratio. The famous mathematician Luca Pacioli renamed it to '*Divine Proportions'* [17].

Marquardt, American beauty researcher, has developed a "Beauty Mask" based on the golden proportions [20], Figure 2-8.

He believes that although nobody fits this ratio perfectly, women, especially the most attractive one, fit it the best. Surgeons found this mask credible and it fits properly on Asian and white women, but among the black skin people for non-European populations such as sub-Saharan Africans and East Asians the mask does not match well.

There have also been attempts to correlate ideal facial proportions with the Golden proportion. However, the faces of professional models have not been found always to fit the golden Proportion, and a study looking at the aesthetic improvement of patients undergoing orthogenetic surgery found that, while most subjects were considered more aesthetic after treatment than before, the proportions were equally likely to move away from, or toward, the olden Proportion.

Figure 2-9 Stephen Marquardt's beauty mask applied to attractive women from different nations[1]

2.2.3. Computer-based beauty analysis

Most approaches for analyzing beauty are either holistic or feature based. The aim of holistic approaches like PCA (Principal Component Analysis), LDA (Linear Discriminant Analysis) and SVM (Support Vector Machines) is to perform an automatic classification algorithm that matches the human subjective ratings which is based on the number of face samples. In feature based approach, features like size and location of face elements are important. Shape, texture, symmetry and averageness are some of the features that have been used in many studies. In the following we explain some methodologies of computer-based beauty analysis.

[1] http://majorityrights.com/weblog/comments/the_facial_proportions_of_beautiful_people/

In artificial intelligence and computer vision it is important to design a machine that can behave and decide like humans in recognizing and analyzing visual concepts such as object recognition, text reading, geometric feature learning, and beauty and so on. One of the most recent concepts in computer vision is beauty even though it is not a new topic in social sciences and it goes back to late 1980s, [21].

In 1990, Langlois and Roggman,[14], tried to find the answer to the question: What makes a face beautiful? Their approach to this problem was to create composite faces from digitized images of male and female faces, average them mathematically and ask people to evaluate them. This revealed that the average faces of males and females were chosen to be the most attractive picture from all, moreover, by providing more samples the average face becomes more attractive. Winkielman and Halberstadt believe that it benefits from familiarity effect [22]. They believe average faces are easier for the brain to process. When our eyes are exposed to a new face, our brain stores the picture for later use. While perceiving more faces the brain attempts to categorize them and find similarities among them, which is the basis of face prototyping. Accordingly beauty would depend on what kind of faces we see [14]. In 1991 Alley et al showed that average faces are not ideal for beauty analysis since the skin quality of averaged face is different and flaws would disappear while averaging, furthermore it is very symmetrical and the symmetry causes beauty (for more details read Symmetry on chapter 2.2.3). They stated that the most average facial appearance is not the most attractive and the aesthetic perspectives are different for men and women, males prefer juvenile facial characteristics for their female mate (Alley, 1988) and females have a preference for remarkable characteristics such as large eyes, cheekbones and chins (Cunningham *et al.* 1990) [23]. Facial symmetry is another concept discussed in 1994 by Grammer and Thornhill (more details about Symmetry on chapter 2.2.3) [24].

Geometric features are mostly the basis of computer science approaches, in which the exact location of landmarks is critical in the feature selection phase. The distance and ratio between these points are used with a classifier to define beauty [25]. In 2001, Arabi *et al* used a vector of 8 ratios between facial features b. A variant k-nearest neighbor algorithm is used to relate the ratios vector to the beauty vector and the photos were rated by a panel of judges with the scores rating from zero to three (3 most beautiful and 0 least beautiful) [26]. In 2006, Eisenthal *et al* used other facial features such as symmetry, skin smoothness and hair color; they assessed their method on two datasets of 92 images with rating of 1-7[25].

Recently computer scientists are focusing on automatic makeup applications. The first research done is by Guo *et al* in 2009. In their study they apply a selected style of makeup from various examples upon a face image. In this automatic makeup application the two images are decomposed into three layers: skin structure, color and detail layer. The advantage of this approach lies in requirement for only one example image and also preserving the face structure while applying the makeup [27].

2.2.3.1. Symmetry

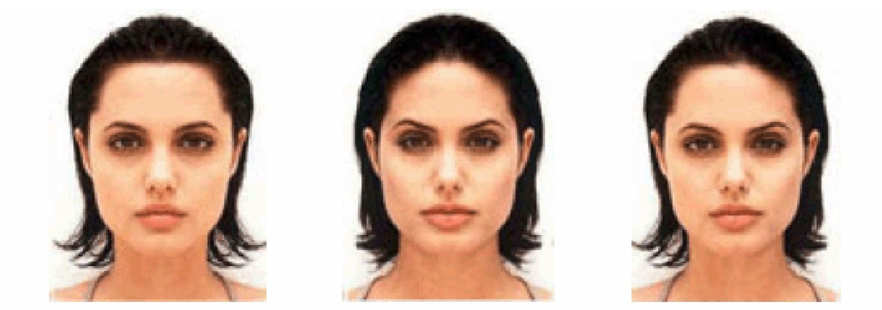

Figure 2-10 Effects of symmetry:
Right) the original; Middle) right symmetry and Left) left symmetry[1]

It is almost unbelievable that symmetry has influence on facial beauty. Many beautiful people have symmetrical face and vice versa. Figure 2-10 displays the effect of symmetry in a face by mirroring picture from left and right. As a result by applying image processing techniques on digital facial images, measuring asymmetry and performing artificial symmetrical on face we would have much more pleasant faces. The effect of symmetry has been studied by many researchers but the result for images with low degrees of asymmetry is controversial. New research in School of Biological Science

University of Liverpool links between athletic ability and look (beauty)[28]. The base of this research is to analyze the symmetry in runner's face. They are trying to find out whether runner champions have symmetrical faces or not. In biology people with more symmetrical body are considered to be healthier[1].

2.2.3.2. Averageness [2]

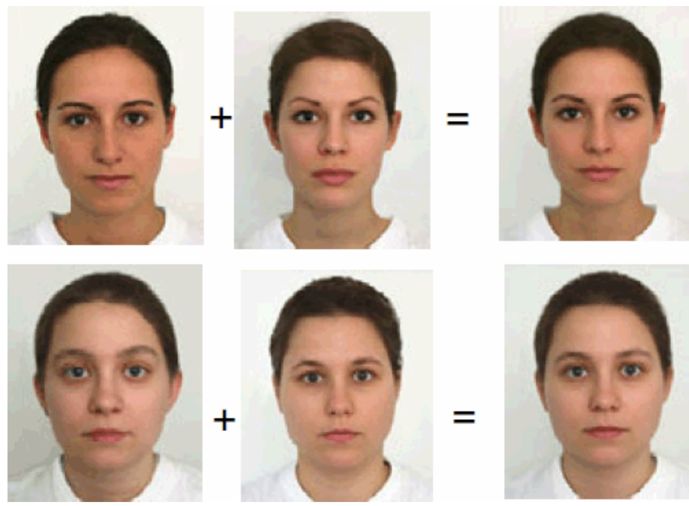

Figure 2-11 Averaging faces [1]

There is some evidence that the more average a face looks, the more attractive it is perceived to be. Donald Symons, an anthropologist, describes the beauty as averageness (the average values of the features of faces in a human population)[29]. Figure 2-11 describes the result of averaging two facial images. The average face obtained with this method was selected as the most beautiful picture among them. His claims are based on evolutionary biology. During periods people with the average physical properties have the most chance to survive. Langlois and Roggman in 1990[14] computerized the process of achieving the average of many human faces. They used the technique developed by Galton[3] a century earlier which was done in an effort to visualize the facial characteristics

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[1] A video about their research in school of Biological Science University of Liverpool: http://www.youtube.com/watch?v=laIv4Kbcz-Q&feature=related

[2] Averageness is one of the characteristics of physical beauty in attractiveness studies.
[3] Galton devoted many years of study on "Composite Portraits", in which photographs of different subjects were combined through repeated limited exposure, to produce a single blended image. He developed

that were common to a particular group of people. The composite faces obtained by the computer graphic techniques are perceived to be more attractive. One explanation for 'Averageness Hypothesis' is that average faces resemble more to mental representation of a typical face, therefore it is easier for the brain to process it. The same thing happens for symmetrical faces. This explanation defines a possible link between attractiveness and the ease with which faces can be processed.

(a) Composite of 60 Faces

(b) Composite of 15 Most Attractive Faces

(c) Hyper-Attractive Composite

Figure 2-12 Comparing attractiveness in average faces[1]

Prerrett et al. (1994),[30], in a classic study of facial attractiveness tested the Averageness Hypothesis. First they collected 60 frontal faces of women in similar conditions. Then the photographs were to be rated from 1 (very unattractive) to 7 (very attractive). Next, they used computer graphic methods to build composite face from the whole sample (60 samples) and a second composite face with the 15 top rated beautiful faces. Finally they created a hyper-attractive average face by exaggerating the differences of the two constructed composite faces, Figure 2-12.

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statistical tools of comparing different population groups like common features among people convicted of crimes of violence.
When he showed the results to people they agreed that these composite faces tended to be more attractive than the individual faces.
[1] http://www.faceresearch.org/students/averageness

Interesting results are obtained after asking people to rate the resulting three faces in Figure 2-12. Participants rated the hyper-attractive face as the most attractive one which is mathematically far from averageness. This finding implies that attractive faces are not necessarily average,[30].

2.3.Make-up

Use of cosmetics and old art has a very long history that is documented almost from 10000 BC on earth. The archaeological evidences show that ancient Egypt was using cosmetics in 4000 BC. Personal appearance and cleanliness was highly regarded by the ancient Egyptians, [31]. Around 1400 BC, in the burials found with three ladies along with costly royal funerary equipment, some cleansing cream was also found. Make-up utensils usage was very popular among Egyptians, Figure 2-13, [32].

Figure 2-13 A lady wiping her face, Relief of unknown provenance; 11th Dynasty

Kohl made up of lead, copper, burned almonds, soot, and other ingredients was used for thickening the eye's outline so that they could move away the evil spirit. In Egypt everyone, males and females were free to use any kind of cosmetics, dye or cut their hair, paint their body or wear skirt. Around 3000 BC in China people painted their fingernails with gum Arabic, gelatine, beeswax and egg. Colors were a tool to show the social level of people. Gold and silver were colors used by *Chou dynasty* and dark colors such as black and red became common for loyal families. In Japan, rice powder was used by the geishas to whiten the face and the safflower powder to color the lips, eyebrows and the corner of eyes, Figure 2-14 [32]. In Europe during the middle age (5^{th} to the 15^{th} century) wearing makeup was believed to be immoral by Church leaders. Besides, most wealthy people did not have to work outside the houses they had white skin. Therefore, having pale skin was considered more beautiful so whitening skin by white powders

Figure 2-14 Japanese traditional make-up[1]

2.3.1. Makeup Techniques

Cosmetics or makeup are substances used to improve the appearance or odour of the human body. Cosmetics include skin-care creams, lotions, powders, perfumes, lipsticks, fingernail and toe nail polish, eye and facial makeup, permanent waves, colored contact lenses, hair colors, hair sprays, gels and so on. A makeup artist is the person, applying makeup and prosthetics for theatrical, television, film, fashion, magazines and other similar productions including all facets of the modeling industry. Makeup artists use various techniques depending on the application. In the following some makeup techniques will be discussed, [33].

[1] Photo from : http://barefacedtruth.com/2012/01/18/a-brief-history-of-skin-care-cosmetics-part-1-ancient-times/

Fashion Makeup

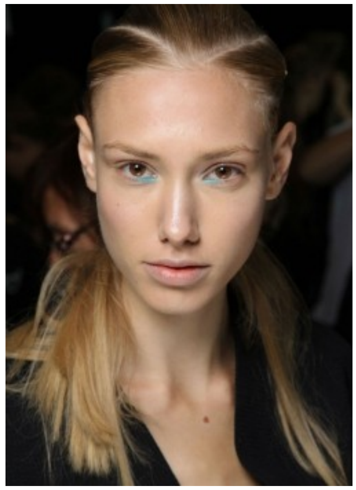


Figure 2-15 Fashion Makeup

Fashion makeup is the type of makeup required for special purposes such as magazines, video promotions and fashion runaways which are specially designed to promote a product, model or special fashion design. Since the viewer for this type of occasions are not far from the model which are exposed to many lights, delicate and careful type of makeup is needed. For this type of makeup usually a professional hair-dresser is needed, Figure 2-15, [34].

Theatrical Makeup

Theatrical makeup or Stage makeup is a special type of makeup for dancers or actors that are on the scene. Special makeup is required for these people because of the stage light. On the stage it is important that spectators feel and see the actors facial expressions, therefore by emphasising more on the eye and lip's colors and adding more highlights and lowlights to face more feeling could be perceived by actor's face, Figure 2-16.

Figure 2-16 Theatrical makeup, before and after[1]

Special Effects Makeup (FX Makeup)

Special Effects Makeup is the use of special effect techniques enhancing physical features to exhibit metaphysical characteristics as well as fantasy makeup. The use of prosthetics and plaster casting are also required for projects that entail non-human appearances. Accents such as theatrical blood and ooze are also techniques applicable to this type of makeup.

Airbrushing

Airbrushing is the use of an airbrush which is a small air-operated device that sprays various media including alcohol and water-based makeup by a process of nebulization. The earliest record of this type of cosmetic application dates back to the 1925 film version of Ben-Hur, it has recently been re-popularized by the advent of HDTV and Digital Photography, wherein the camera focuses on higher depths of detail. Liquid Foundations that are high in coverage but thin in texture are applied with the airbrush for full coverage without a heavy build-up of product.

[1]Photo from: http://dance.about.com/od/youngdancers/ss/Stage_Makeup.htm

High Definition

This is an art which involves the use of light reflectors and ingredients such as minerals to give the skin a flawless finish. This was developed due to the further development of High Definition media and the cost implications of airbrush makeup.

Prosthetic makeup

Prosthetic makeup also called FX prosthesis is the process of using prosthetic sculpting, molding and casting techniques to create advanced cosmetic effects.

Permanent make-up

The idea of permanent makeup sounds appealing... never having to apply eyeliner, lip liner, or other penciled makeup techniques again sounds good, [35].Permanent makeup is a form of tattooing and there are dangers and consequences from tattoos that must be considered. Additionally, 'permanent' makeup means just that: permanent.

2.3.2. Computer-based Makeup analysis

There is not much work addressing digital face makeup. In 2007 Tong *et al* developed Example-Based Cosmetic Transfer that learns how the face changes before and after makeup [3]. In Figure 2-17 only the cosmetic style from the Asian woman is transferred to European woman. Skin tone and personal features such as eyebrows and eyelashes in B are preserved after the transfer. Therefore the photo before makeup and the photo of the person with the professional makeup are required to train the system. Their approach can be used to transfer the makeup from one image to another with the need for any physical makeup. This approach contains of 4 steps: 1) pre-processing, 2) cosmetic mapping, 3) appearance correction, and 4) eye transfer. In the second phase, the quotient matrix obtained by $c_p = a_p{}^* / a_p$ where a_p and $a_p{}^*$ are the respective intensity before and after makeup. After computing the collection of all c_ps it will be applied to the target face B with the formula: $a_p{}^* = c_p b_p$where $b_p$is the target face pixel. The complex part is to transfer the makeup of the eye to the target face because of the eyebrows and eyelashes.

Their proposed method for transferring makeup, preserves the skin tone, skin texture, facial hair color and hair density.

Figure 2-17 Example-based cosmetic transfer. A and A* are the "before-and-after" makeup images of an woman of Asian descent. B is an image of a woman of European descent. B* is our result, after transferring the cosmetic style depicted in A*

Another approach for transferring makeup is proposed by Ojima *et al.* [36]. This method basically needs two images before and after makeup. They extract the haemoglobin and melanin information of the skin which they use them to apply on the new images to show the effect of tanning and alcohol consumption, see Figure 2-18. It is possible to apply the technique to convert back the skin of a 50 year-old woman to 20 year-old.

Figure 2-18 Alcohol consumption: (a) original image, (b) synthesized image and (c) real image after alcohol consumption

Guo *et al.* [37] introduced a method to apply digital face makeup to a picture just by having an example picture. In contrast to other approaches a "before" image is not required. The workflow consists of four main steps. First the face alignment should be done for both the example and the source image. Followed is a layer decomposition, which decomposes the faces into three layers: face structure layer, skin detain layer, and the color layer. The face structure of both source and the image will be transferred by gradient editing. The skin detail of both images is transferred in an additive way and the color will be transferred by alpha blending. Finally, three resultant layers are composed together.

In Conclusion, many approaches have been proposed to identify beauty (described in section 2.2.3) and few to transfer makeup to a new picture but none of them recognizes if the individual has makeup or not. In this thesis, besides recognising the existence of makeup it detects the locations of makeup as well. The similarity of all the approaches introduced here is that they decompose the information of face to two parts: skin and texture. In the following chapter, the new collected facial makeup database will be introduced. A comparison of the available public databases will be introduced as well.

Chapter 3

3. Facial Makeup Database

Appropriate database plays an essential role in classification of any machine learning or data mining task. It is needed in all the steps of image processing such as feature extraction, training and testing. Therefore it is critical to choose a database that is suitable for the application. In face recognition and face analysis applications, it is critical to have a database which covers all possible variations of the target environment, for example if the aim of an application is to recognize human faces in videos, the database should contain videos of people in different lighting (with partial of complete shadow), distances and objects in the frame.

Validation of a technique for a specific problem furthermore depends on the chosen database. Therefore while comparing the results obtained from different methods, the same database should be used. In digital makeup detection, this is the first step in this research, because there is no other database or result available to compare with. Although many published facial databases are for public use, none of them is specifically designed for makeup detection purposes. In the following section some of them will be discussed.

3.1.Published Facial Databases

Since facial analysis is of high interest in pattern recognition and machine intelligence topics, a lot of time and effort have been spent on providing facial databases. Facial databases are application-specific but sometimes the collectors of databases include more information in case in the future it is helpful for other purposes as well. Many face databases are available for public but none of them is for makeup purposes. Face recognition, gesture recognition, age estimation and age progression are some applications of such face databases. In this section some famous facial databases are introduced and finally the database collected for this research will be discussed.

Table 3-1 Public facial databases [38]

Name	Color	Size	No. Participants	View	Description
AR Face	Yes	576x768	116	frontal	Different facial expressions, illumination conditions and occlusions. No restriction on wearing makeup, scarf, sunglasses…
Richard's MIT	Yes	480 x 640	154	frontal profile, 3/4	
CVL	Yes	640 x 480	114	Frontal...	profile left/right, 45 degrees left/right, frontal, frontal smile, frontal smile with teeth
Labeled Faces in the Wild	Yes	150 x 150	13,233	Un-posed	Un-posed but mainly frontal

MUCT	Yes	480 x 640	276	frontal 3-quarter	different lighting sets, manual landmarks
Yale B	No	640x480	10	9 poses	9 poses x 64 illumination conditions
Yale	No	320 x 243	15	frontal	center-light, w/glasses, happy, left-light, w/no glasses, normal, right-light, sad, sleepy, surprised, wink
PIE	Yes	640 x 486	68	13 poses	43 different illumination conditions, and with 4 different expressions.
UMIST	No	220 x 220	20	Various angles	
Olivetti - Att - ORL	No	92 x 112	40	frontal	
Japanese Female Facial Expression (JAFFE)	No	256 x 256	10	frontal	7 different emotional facial expressions
Human Scan	No	384 x 286	23	Mainly frontal	random different photos of different people
University of Oulu Physics-Based	Yes	428 x 569	125	frontal	16 different camera calibration and illuminations

Since human face has a complex 3D structure and non-rigidity property, it would be influenced by many factors such as age, facial expression, illumination, face pose... However the algorithms are robust to such changes in photos, databases should be carefully collected under controlled conditions. Table 3-1gives an overview of published databases with the controlling factors.

Figure 3-1 Sample images from the database of before and after makeup

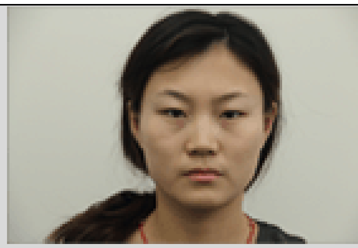
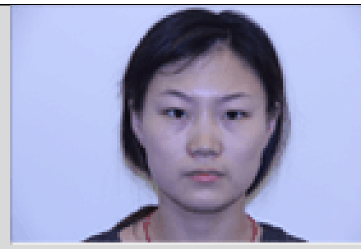
3.2.Collected New Facial Makeup Database

In this research for the purpose of makeup detection in women's face images, a facial database is collected from women before and after applying makeup. In a four month period looking for participants, 21 women participated. The faces are all frontal faces with white background. The images are all 2D colourful and are taken by a Canon T2i, 18MP camera. The camera was set to RAW and White balance was manual for each subject. Images were all taken under the same controlled indoor environment.

From each participant, 2 sets of images are taken, the first set is without makeup and the second set is with makeup (Figure 3-1). In each set we have two types of lighting; one type with indoor lighting and one spot light (Figure 3-2) and in the other type without indoor lighting but only a single spot light (Figure 3-2).

From each participant, 60 images before makeup (Figure 3-2 and Figure 3-3) and 60 images after makeup are captured. In order to have pictures with open eyes and not with blinking or closed eyes, two shots were taken from each situation. The dimension and the size of original image are 2074x1382 and 1.87 MB respectively. But for the research the dimension 380x480 pixels and the size 91.0 KB are used.

Figure 3-2 Images of one participant before makeup and with indoor lighting from different spot light directions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		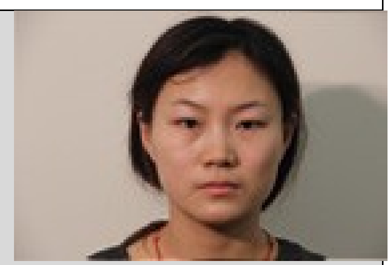
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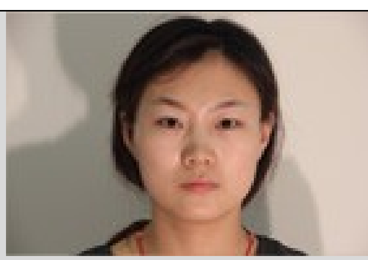	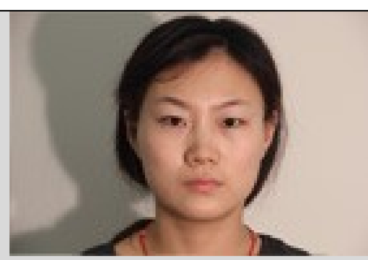	
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P0021_026_RR-BT-O-SL-N-00	P0021_028_RR-MD-O-SL-N-00	P0021_030_RR-TP-O-SL-N-00

Figure 3-3 Photos of one participant before makeup and without indoor lighting from different spot light directions

		
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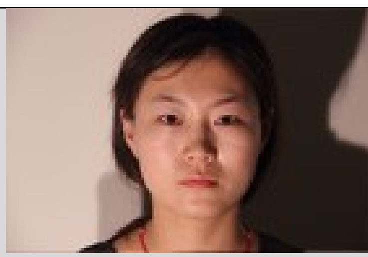		
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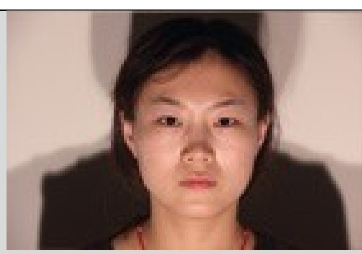
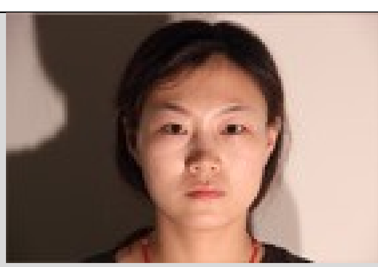
		
P0021_044_CC-BT-F-SL-N-00	P0021_046_CC-TP-F-SL-N-00	P0021_014_L4-TP-O-SL-N-00
		

P0021_048_R4-BT-F-SL-N-00	P0021_050_R4-MD-F-SL-N-00	P0021_052_R4-TP-F-SL-N-00
		
P0021_054_RR-BT-F-SL-N-00	P0021_056_RR-MD-F-SL-N-00	P0021_058_RR-TP-F-SL-N-00

To facilitate the process of extracting information from the photos such as lighting direction, with/without makeup, with/without flash and with/without indoor light a convention is used to name the photos.

Naming convention for the images of makeup database:

- CC=Centre, LL=Left 90 Degrees, L4=Left 45 Degrees, R4=Right 45 Degrees, RR=Right 90 Degrees
- MD=Middle, BT=Bottom, TP=Top
- O=Main Lights On, F-Main Lights Off
- NF=No Flash, WF=With Flash, SL=Spotlight
- N=No Makeup, Y=With Makeup
- 00-First Shot, 01=Second Shot

Figure 3-4 represents sample images from the makeup database after makeup. The name under each image explains how the naming convention is defined for them.

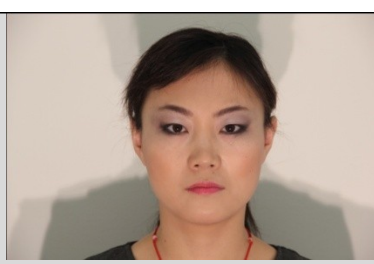
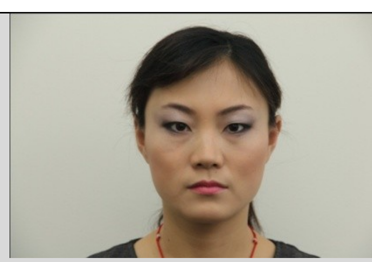
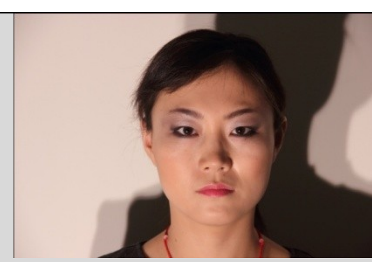
		
P0021_076_CC-BT-O-SL-Y-00	P0021_061_CC-MD-O-NF-Y-01	P0021_098_L4-BT-F-SL-Y-00

Figure 3-4 Sample images from the makeup database, after makeup with their names

3.2.1. Participants

Participants mostly consisted of students and staff at Concordia University. The respondents were recruited through e-mail and posters at Concordia University. In total 21 women participated in the research.

Table 3-2 Participant's information from Makeup database

Participant	Ethnicity	Country	Age	Smoking	Drinking
#0	Iranian	Iran	30	No	No
#1	African	Ghanaian	26	No	Occasionally
#2	Iranian	Iran	31	No	Rarely
#3	Latin American	Elsalvador	31	No	Socially
#4	Polish	Poland	60	No	Socially
#5	Iranian	Iran	41	No	No
#6	Iranian	Iran	38	No	No
#7	Latin	Colombia	31	No	Socially
#8	Iranian	Iran	34	Occasionally	Socially
#9	Iranian	Iran	39	Occasionally	Rarely
#10	Iranian	Iran	38	No	Socially
#11	Iranian	Iran	60	No	Rarely
#12	Iranian	Iran	64	No	No
#13	Iranian	Iran	25	No	Rarely
#14	Colombian	Colombia	41	Occasionally	Socially
#15	Moldovian	Moldova	29	No	Rarely
#16	Iranian	Iran	24	No	Rarely
#17	Iranian	Iran	24	No	Rarely
#18	Asian	Chinese	23	No	Rarely
#19	Asian	Chinese	26	No	Socially
#20	Asian	Chinese	23	No	Rarely

As can be seen from Table 3-2 most of the participants' ages are 20 to 40 and most of them are Iranian and Chinese.

3.2.2. Meta Data

In order to make the database useful for other applications as well, some meta data is provided along with the makeup information. This information consists of ethnicity, country, smoking habits, drinking habits, age, and job. Some information like smoking and drinking habits may be helpful for age estimation.

3.2.3. Makeup

Applying the best type of makeup for the participants was of major concern when collecting the makeup database. The type of makeup applied on the participants' face were chosen to suite two different goals first to apply changes on the face in order to be able to study the face from the pattern recognition point of view and second to make them beautiful for study from aesthetician purposes. Although human faces share the same face features (such as eyes, eyebrows, nose and lips), the size, shape and distance of each plays an important role in beauty perceived by them. Makeup is a powerful art in covering the face defects and showing youthful and more appealing face but not every type of makeup will be pleasing in every face. Professional makeup artists are experts in choosing the best makeup style that reveals the person's beauty. Color of cosmetics is another important factor in makeup since individuals have different colors for their skin, hair and eye. Choosing the proper color for the cosmetic highly depends on the knowledge and experience of the makeup specialist. In this section the methods and techniques to apply makeup for participants' face will be discussed.

3.2.3.1. Eye Makeup

Eye is the most prominent feature in the face. The best makeup artists know how to make eyes more beautiful so that the whole face looks more interesting. To have beautiful eyes cosmetics like eye-liner, eye-shadow, eyebrow-shadow, mascara and curling eyelashes are essential. Use of colors in makeup helps the face feature to look deeper, closer or larger.

Depending on the eye's shape and distance, proper makeup should be applied. Makeup artists categorize eyes to seven types which will be discussed in the following section. These rules are applied on participant's face for this database [39].

1- Wide Set Eyes

People who have a greater distance between their eyes are considered to have wide set eyes. For this type of eye by use of dark eye shadows in the inner corner of eyelid and applying that softly to the bridge of nose, it would be possible to almost hide the extra distance. Mascara also should be applied on both upper and lower lashes. For this type of eyes bright colors for the outer edge under the brow should be avoided since it would pull the eyes outward, Figure 3-5.

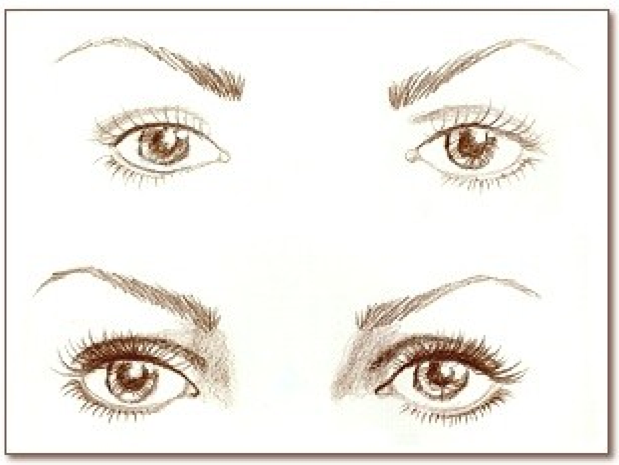


Figure 3-5 Wide set eyes and the appropriate makeup [39]

2- Close Set Eyes

Close set eyes are those which are narrower than one eye width, Figure 3-6. For this type of eye to look normal, the outer corner of eyes should become darker.

First eyeliner should be applied to make a thin layer around the outer corner of eyes along the upper eyelashes. Then the dark eye shadow should be smoothly put from center to the outer corner of eyelids. Light color of eye shadow should be put from inner corner to the middle of eyelids. Mascara is needed for both upper and lower lashes, but more on the outer corners.

Figure 3-6 Close set eyes and the appropriate makeup [39]

3- Deep Set Eyes

In deep set eyes, they look deeper in the face, so bright color eye shadows will be helpful to make the eyes appear bigger. In order to do that bright color should be applied to the inner corner of eye and a bit upward and further. For above the socket line dark color has to be put softly to a bit up. A shade of very bright color is also needed under the brow, Figure 3-7.

Figure 3-7 Deep set eyes and the appropriate makeup [39]

It is important to avoid dark colors on the brow bone since it would make the eyes even look deeper. Moreover eyeliner for top eye lid is not recommended.

4- Hooded Eyes

Figure 3-8 Hooded set eyes and the appropriate makeup [39]

In hooded eyes, eyelids are partly covered by skin hung over socket line and moveable eyelid is always hidden. For this type, the makeup should be very simple and dark to medium shadow should be applied on the hooded area. For the rest only light colors, since the use of dark colors make the eye look deeper. Plenty of mascara and fake eyelashes for the top eyelid is also recommended.

5- Asian Eyes

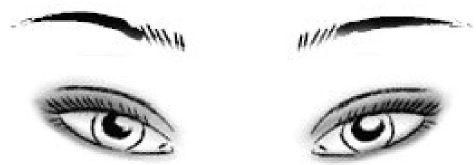


Figure 3-9 Asian eyes

These eyes have a unique lift at the outer corners of eyes. To make the eyelids look larger very light shadows should be applied. But to make the eyes look larger a very smoky line around both upper and lower eyelashes is needed.

A thin layer of eyeliner for the bottom eyelashes line and two or three layers of mascara are also useful.

6- Small Eyes

Figure 3-10 Small eyes and the appropriate makeup [39]

They are proportionately smaller in comparison to the rest of the facial features. To enhance small eyes, a dark color should be applied to the crease and light shadow on the eyelid. Eyeliner for both upper and lower lash lines is needed. Black mascara on upper lashes will also make the eyes look larger, Figure 3-10.

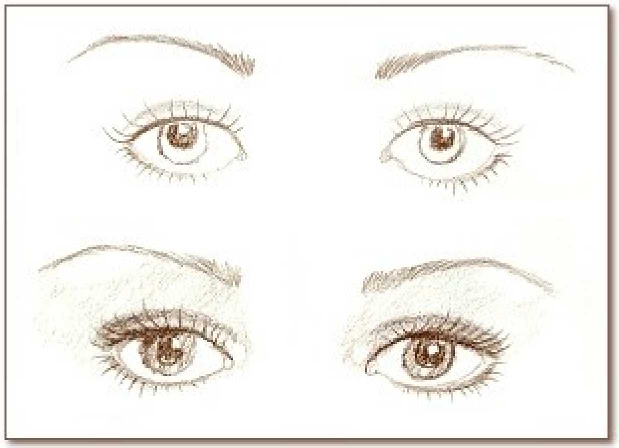


Figure 3-11 Prominent eyes and the appropriate makeup [39]

7- Prominent eyes

In this type of eye set the eyelids are too large. Medium to deep shades of shadow on the lids help to minimize the appearance of lids. Liner when applied to the lash bases from corner to corner gives prominent eyes a mysterious look. A coat of black mascara on both upper and lower lashes will produce a nicer look.

3.2.3.2. Lip Makeup

No makeup is finished without a lipstick color. There are different cosmetics used for lips such liquid/solid lipstick, lip pencil and lipstick brush. Depending on the lip shape and skin color different techniques can be used. Lipsticks can give different looks: matte, satin and gloss, however for this study only matte lipstick is used. Matte lipstick has little shine and lasts more; furthermore it shows more in digital images.

3.2.3.3. Face-Skin Cover up

Human face skin, being exposed to sunlight, cosmetics and bad living habits like smoking and drinking, is so prone to acnes and wrinkles. Therefore for some skin types it is necessary to cover up the defects by means of cosmetics. Makeup artists benefit from the following cosmetics for face skin:

- **Liquid foundation**: if natural and close to skin color is chosen, blends with skin color and makes skin look more uniform in color. It helps to cover birthmarks and scars.
- **Powder**: used usually after (or sometimes alone) liquid foundation to wipe out the shiny look of liquid foundation. It helps to give a nice matte finish to face and helps the makeup to last longer.
- **Concealer** (color corrector): used to mask the dark circle color under the eyes, pimples and broken veins

Although in digital imaging the skin defects can totally be covered but in real life by use of these three cosmetics a very nice and smooth skin tone can be created, Figure 3-12.

Figure 3-12 Covering face skin defects by liquid foundation and powder (before and after)

In this chapter the process of creating a new facial makeup database was described. Different levels of makeup with different colors were applied on the faces in order to have various changes on the faces. At the time of applying makeup beauty was considered as well, since it was important to use the database for other purposes such as beauty as well. Therefore the effect of makeup on attractiveness of women can be studies with this database.

Over 1300 images are collected for this research. Large portion of these pictures are used for the training and testing phases, since many of the pictures contain variations to lighting which is not suitable for makeup detection. The naming convention was also introduced and used for the pictures, which facilitates the study of makeup on the images.

In the next chapter the methodology to extract features will be described. However before any process the landmarks should be located on face. Afterward, the landmarks are saved in the appropriate CSV (Comma Separated Values) files. After landmark detection some pre-processing such as color adjustment and face alignment should be applied on face. Two categories of features will be described: the color information and the texture information. The features extracted from the faces will be then used in classifier.

Chapter 4

4. Facial Feature Extraction

Feature Selection is one the most important phases in machine learning and classification systems, which consists of selecting the best subset of attributes that yields the best result for classification. Analyzing face beauty by computer has been of great importance in recent years (discussed in section 2.2.3). Besides, the use of makeup is increasing to a great extent each year. Therefore designing an algorithm that helps aestheticians to analyze the individual's makeup by extracting it and helps them to suggest the best type of makeup that matches to person's face and makes her more appealing, can be very valuable. This will reduce the time and money spent on trying many different cosmetics to reach the best result. This would also be helpful in security systems to better identify people wearing plenty of makeup.

After collecting the face images of women before and after makeup and gathering enough number of pictures, it is time to start processing them. In most image processing applications the data should be prepared with some pre-processing techniques. The number of images and the amount of data to be processed affect analyzing and classification time. In the classification phase, choosing the appropriate features is the main concern since bad features can mislead the classifier.

In this chapter, the proposed system to analyze makeup by computer and features like color characteristics and texture information that are used in this research will be discussed.

The common parts in face that usually get makeup are the eye lids, lips and cheek, Figure 4-1. In this research the focus of this study is more on eyes and lips. The input of this system is colourful frontal images of face and the output will be to recognize if the person has makeup or not.

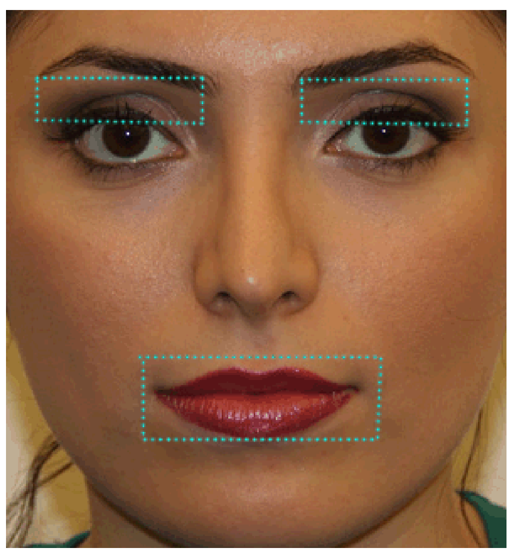


Figure 4-1 Common targets of makeup

Although there are varieties of makeup types (discussed in section 2.3) .The focus of this research is the common type of makeup that most women wear nowadays. As such, the eye/eyebrow tattoos and piercing are not considered in this research. The most probable areas which are target for makeup are shown in Figure 4-1. Depending on the individual's taste and need, one or all of the specified locations could have makeup. The following issues could be examined in analysing makeup:

- Checking skin quality to see if she has foundation
- Checking cheek color, usually red or pink color are used
- Comparing eyelid color with forehead to see if it is shiny or colorful, because this place has no makeup except the foundation cream
- Checking if she has eye liner
- Checking lips to see if they are shiny or have lipstick

4.1. Preparing inputs

The first and important part of most image processing and pattern recognition researches is database. In this study we benefit our own collected database but generally we can use any frontal face images of women who have or have not makeup that is indicated in database. The facial makeup database collected for this study has 780 images of different level of makeup, lighting, age, and ethnicity. More details about the database is described in section 3.2 (Collected New Facial Makeup Database).

As discussed in section 3.2, the database contains many variations of lighting which is not the goal of this study, therefore, only the images with one frontal spot light are used. After eliminating unrelated images 110 images were left for the study. In order to simplify the analytics and use of the database, photos of each individual is put in the same folder; moreover the photo's naming contains useful information about the makeup and lighting condition, so when processing each photo it is straightforward to know which faces have makeup and which do not.

4.2. Landmark Detection

The next step after collecting the database is to find face landmarks. Landmarks are distinguishable points on face that help to describe a shape. In this application it facilitates the process of finding the face features such as eyes, nose or lips. The complexity in detection usually arises from the variations of human faces caused by expression, hair, glass, poses and also surrounding conditions such as lighting, existence of similar objects or even the quality of images and also faces deformation caused by expressions and speaking. We focus mostly on the frontal views of upright faces. In Figure 4-2 the dots represent the 68 face landmarks found by Active Shape Models algorithm, which will be discussed in section 4.2.3.

In this study a top-down model based approach is used to identify landmarks. Model can be built by analysing the appearance of a set of labelled examples. Models can also cope with the variability. For new images it attempts to find the best reasonable match of the model to the image data.

Figure 4-2 Facial landmarks

4.2.1. Previous Works

Traditional recognition systems have the ability to recognize the human using various techniques like feature based recognition, face geometry based recognition, classifier design and model based methods. History of face recognition and its relation to faces started in 1960 with semi automated systems. One of the methods to do face recognition is to look at the major features of the face and compare them to the same features on other faces. Marks were made on photographs to locate the major features such as eyes, ears, noses, and mouths. Then distances and ratios were computed from these marks to a common reference point and compared to reference data. In the early 1970's Goldstein, Harmon and Lesk created a system of subjective markers such as hair color and lip thickness. This proved even harder to automate due to the subjective nature of many of the measurements still made completely by hand, [40].

Linear subspace methods like Principal Components Analysis (PCA) were firstly used by Sirvovich and Kirby [41], which were latterly adopted by M. Turk and A. Pent Land introducing the famous idea of Eigen faces [42], [43]. There are many algorithms that have been proposed for facial landmark location. As suggested by Hamouz et al. [44], they can be classified in two categories: image-based and structure-based methods. Structure-based methods use prior knowledge about facial landmark positions, and constrain the landmark search by heuristic rules that involve angles, distances, and areas. The face is represented by a complete model of appearance consisting of points and arcs connecting these points [45]. For each point of this model, a description of these features is associated. Typical methods include Active Shape Models and Active Appearance models. These methods are well suited for precise localization [46].

4.2.2. Suitable Landmarks

Good landmarks are points of high curvature or junctions. Intermediate points can be used to define boundary more precisely.

The connectivity and how the landmarks are joined to form the boundaries in the image. This allows us to determine the direction of the boundary as:

$\{(x_1, y_1), (x_2, y_2), \ldots, (x_n, y_n)\}$.

With K training examples we will have K vectors xj. The shape of an object is normally considered to be independent of the position, orientation and scale of that object. A square, when rotated, scaled and translated, remains a square, and we have to keep the distance $d = \sum |xi - \overline{x}|\, 2$ as a minimum value.

4.2.3. Active shape model

In this project the statistical models of shape is used. Shape analysis is an active area in computer vision. Many researches in recent years have been proposed for shape among them, the Active Shape Model (ASM) is the most flexible methodology and has been deeply researched. The ASM method proposed by Coots[47], represents the shape of an object using a number of landmark points, and the shape variations of the object using Principal Component Analysis (PCA) which forms the point distribution model (PDM). ASM captures the specific characteristics of a shape and its variations are represented by a statistical shape model.

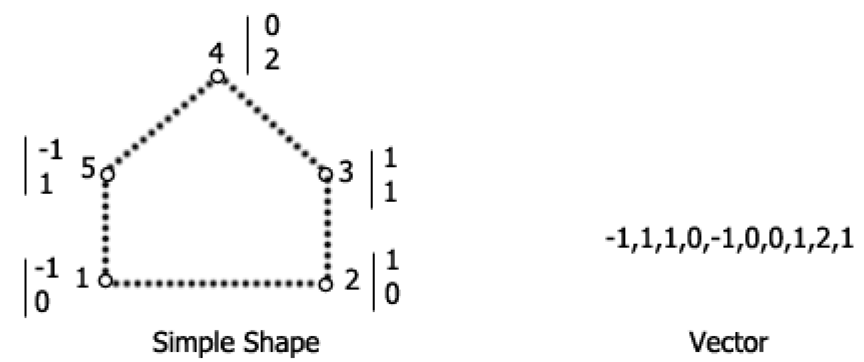


Figure 4-3 Putting shape coordinates in a vector;
Left) a simple shape and Right) the points' coordination in a vector

Active Shape Models like many other pattern recognition methods needs training. After training the system ASM can search for features on face. ASM first tries to locate the landmarks independently, and then tries to correct the location of the landmark with respect to other landmarks. A set of landmarks forms a *shape* which is represented as vectors: all the x-followed by all the y-coordinates of the points in the shape, Figure 4-3 [48].

Shapes must be aligned with some similarity transforms such as: translation, scaling and rotation. These transformations minimize the average Euclidean distance between shape points [47].

The ASM is first trained on a set of manually landmarked images. Manually landmark means that somebody has to mark all the images by hand, which is done before the training phase. After training, the ASM can be used to search for features on a face. The general idea is (1) try to locate each landmark independently, (2) correct the locations if necessary by looking at how the landmarks are located with respect to each other.

4.2.4. Shapes

Mikkel B. et al define shape as "*all the geometrical information that remains when location, scale and rotational effects are filtered out from an object*" [49]. This definition means any Euclidean similarity transform on shape preserves the angles and parallel lines.

If a shape is represented by n landmark points $\{(x_i, y_i)\}$ as a $2n$-D element vector $X = (x_1, y_1, .., x_n, y_n)^T$ then the training shape S would be: $S = \{X_i\}$. As is shown in Figure 4-3, an array of (x, y) coordinates could be changed to n*2 ordered set of points. It would be more convenient in practice to present a 2n*1 vector instead of n*2 array (first all the x and then all the y coordinates afterward).

In this section some mathematical terms that are required for the algorithm will be defined:

- *Euclidean distance between two points*: $\sqrt{(x1 - x2)^2 + (y1 - y2)^2}$
- *Shape distance* between two shapes S1 and S2: the sum of the Euclidean distances between their corresponding points.
- *Centroid $\bar{x}$ of a shape*: the mean of the point positions

- *Singular Value Decomposition (SVD)*:the decomposition of a matrix A $= UDV^T$ so that U is the eigenvectors of AA^T and Vis the eigenvector of $A^T A$

4.2.5. Aligning shapes

The first step in processing the available landmarks is to align the shapes. The goal here is to minimize some of the distances between the shapes and the mean shape $D = \sum|x - \overline{\mathrm{x}}|^2$, which is done by similarity transformation[1]. In order to align shapes, one image (which can be the first shape) should be chosen as a reference shape and then align other shapes to that one. The only transforms that is used is scaling, rotating and linear translation.

The formula for similarity transformation that does the rotation θ, the scale s and the translation (x_t, y_t) is as following[50]:

$$T\binom{x}{y} = \binom{x_t}{y_t} + \begin{pmatrix} s\cos\theta & s\sin\theta \\ -s\sin\theta & s\cos\theta \end{pmatrix}\binom{x}{y}$$

The translation is necessary to put each shape in its origin, therefore mass center of the points will be subtracted from the original location. This would lead the shapes to have a common center.

The scaling part is done by shrinking the size of shape but this would preserve the ratio of shape proportions. Normalization is the best approach to scale the shapes

In order to calculate the rotation matrix for the shape $x_i$with respect to shape x_j, the Singular Value Decomposition (SVD), UDV^T, of ${x_i}^T x_j$ has to be computed. The rotation matrix therefore would be:

$$VU^T = \begin{bmatrix} \cos\theta & -\sin\theta \\ \sin\theta & \cos\theta \end{bmatrix}$$

[1] Two matrix A and B are similar if $B = P^{-1}\, A\, P$ then P is called similarity transformation.

After translation, rotation and expanding, the shape still has the same structure. The algorithm to align all the landmarks for images is[1] [50]:

“**Input** set of unaligned shapes algorithm

1. Choose a reference shape (usually the first shape)
2. Translate each shape so that it is centered on the origin
3. Scale the reference shape to unit size. Call this shape $\overline{\boldsymbol{x}}_0$, the initial mean shape.

Repeat

4. Align all shapes to the mean shape
5. Recalculate the mean shape from the aligned shapes
6. Constrain the current mean shape (align to $\overline{\mathbf{x}}_0$, scale to unit size)
7. Until convergence (i.e. mean shape does not change much)

Output set of aligned shapes, and mean shape”

4.2.6. Profile Model

The job of the profile model is to take an approximate face shape and suggest a better shape by template matching at the landmarks in one dimensional profile.

A *profile* is a 1-D vector which describes the characteristics of the image around the landmark, Figure 4-4. Therefore it is built for each landmark. During training, we sample the area around each landmark to build a profile model for the landmark. Therefore the area in the vicinity of each tentative landmark is searched and the landmark is moved to the position that best matches that landmark's model profile.

To form the profile vector **g** at a landmark, image intensities is sampled along a one-dimensional whisker. A *whisker* is a vector at a landmark which is orthogonal to a shape

[1] The idea for this algorithm derives from Generalized Procrustes Analysis (GPA) a method in statistical analysis used to determine the shape correspondence.

edge. First, g is filled by its correspondent intensity values. Then each element of g is replaced by the difference between its own value and the value of the previous one. At the last stage, for normalization all elements are divided by the sum of absolute values of all vector elements. The purpose of the final step is to lessen the effect of varying image lighting and contrast.

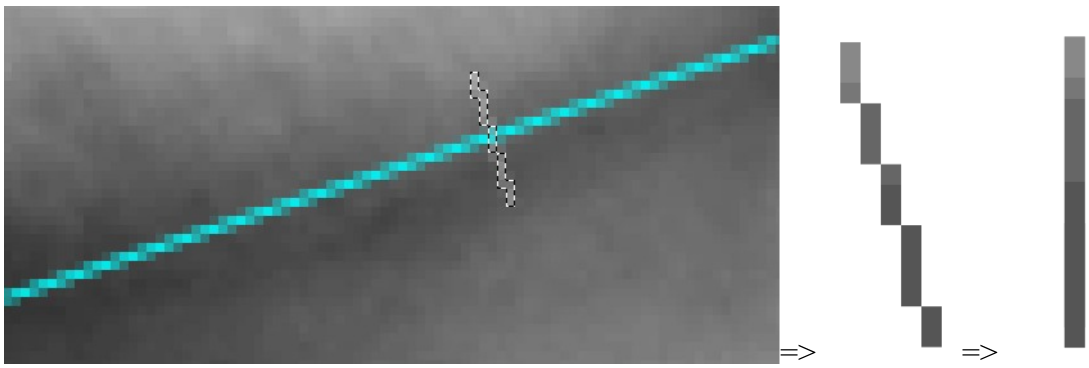


Figure 4-4 An example of one-dimensional profile

As it is shown in Figure 4-4, the blue line is the edge of the shape. The dashed line is the whisker or sometimes it is called normal and it is perpendicular to the boundary. The landmark is at the intersection of the shape boundary and the whisker. The horizontal gray bar shows the image intensity along the whisker which is used to form a profile.

The next step is to find a statistical model of areas around the landmarks. Each profile is stored in a 1D vector and then the average of profiles $\bar{g}$ and the covariance of profiles S_g should be calculated. If the profile $\bar{g}$ has 7 elements then S_g will be a 7*7 matrix. If there are 68 landmarks then there will be 68 separate $\bar{g}$'s and S_g's.

4.2.7. ASM search algorithm

Once all the required information about the shape and statistical data around each profile is collected, it is time to search for landmarks. PCA (Principal Component Analysis) is sometimes used at this step to reduce the dimensionality from $2n-D$ space to $2n-4D$ space. PCA is a technique of expressing a high dimensional data set via an alternative set of dimensions that are orthogonal to each other. Projecting images into eigenspace is a standard procedure for many appearance based object recognition algorithms. Eigenspace is calculated by identifying the eigenvectors of the covariance matrix derived from a set of training images [51].

In order to search for landmarks in a new image, the following algorithm is the main strategy to find the points:

Input: An image of a face

1. Generate the start shape by locating the overall position of the face Repeat
2. Suggest a new shape by profile matching around each shape point.
3. Adjust the suggested shape to conform to the Shape Model
4. Until convergence (i.e. until no further improvements in _t are possible)

Output: shape giving the (x, y) coordinates of the face landmarks"

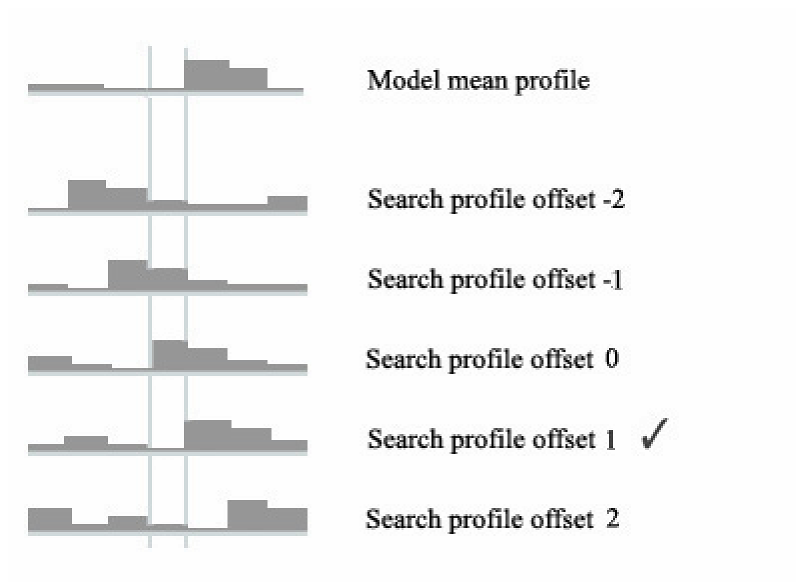


Figure 4-5 Searching for best profile with +/- 2pixel offset

The first step (locating a face), is usually done by available libraries like OpenCv. In the second step, for searching the best profile it is very important to find the best match otherwise it would affect the whole searching process.

Each search profile is centered at small positive or negative displacements along the whisker. We typically form profiles at offsets up to about +-3 pixels along the whisker, Figure 4-5. Next we choose the best of newly built profiles by means of the Mahalanobis distance. The *Mahalanobis distance* between a search profile g and the model mean profile of $\bar{g}$, S_g is the covariance matrix below:

$$Distance = (g - \bar{g})^T S_g^{-1} (g - \bar{g})$$

One of the search profiles will have the lowest distance which is suitable for the new shape.

4.2.8. Fitting a Model to New Points

Models are built by using the main parameter, b (the shape vector). One specific value of b is one point in the rotated space made by P (eigenvectors). Therefore it corresponds to an example model. This can be turned into an example shape using the transformation from the model coordinate frame to the image coordinate frame. Typically this will be a Euclidean transformation defining the position, (X_t, Y_t), orientation, θ, and scale, s, of the model in the image.

The positions of the model points in the image, X, are then given by:

$$X = T_{X_t, Y_t, s, \Theta}(\bar{x} + Pb)$$

T is a similarity transformation. (X_t, Y_t) is the translated coordinate pair. S is the scaling parameter and θ is the rotation parameter. If we apply T to a single point (x, y) it would be as follows (Described in section 4.2.5):

$$T\begin{pmatrix} x \\ y \end{pmatrix} = \begin{pmatrix} x_t \\ y_t \end{pmatrix} + \begin{pmatrix} s\cos\theta & s\sin\theta \\ -s\sin\theta & s\cos\theta \end{pmatrix}\begin{pmatrix} x \\ y \end{pmatrix}$$

The best matching of a model instance, X to a new set of image points Y is made by minimizing the sum of square distances between the corresponding model and image points is equivalent to minimizing the following expression[13]:

$$\left|Y - T_{X_t,Y_t,s,\Theta}(\bar{x} + Pb)\right|^2$$

4.2.9. Results

In Images with high quality the algorithm gave a very good result. Many movements were made during the first iteration to find the position of landmarks. The final convergence was almost after 19 iterations. The initial place of landmarks was very effective in defining the correct landmarks, but it failed to find the correct place if the initial face is totally over positioned. For images with low quality finding the edges is difficult. Shadows on half of the face are a major problem. The ASM technique is a very efficient method to locate the boundary of an object similar to the images available in training set.

An active shape model is a applicable algorithm for finding the boundary of object with fine boundary such as hands. But it fails for widely varying object shapes. Improvement of active shape model is Active Appearance Model (AAM) which matches an appearance to a new image[48]. They are built during a training phase. So it can be use for matching and tracking faces.

4.3. Pre-processing

Image processing and pattern recognition is highly sensitive to the input quality, therefore pre-processing plays an important role in acquiring promising result. In face recognition many issues can affect analysing the face. Illumination is one of the major problems in face analysis, excess brightness or darkness creates unwanted patterns on face. Accessories such as glasses or hat partially cover the face, causing problem recognizing the face structure. Face gesture and face orientation are other problems in facial analysis. In this study frontal faces with indoor lighting conditions are used but the problem with bad orientation and unsuitable color remains which have to be corrected. First thing about the images is to reduce the size and dimensionality since it increases the process time. The images are cropped to facial area and resized to 380x480 pixels.

Figure 4-6 Histogram Equalization:
Left)Source imag and Right) Result after histogram equalization

4.3.1. Face Alignment

The next step is to straighten the face since the disorientations of the face cause difficulties in calculating the face feature's area. Since this step is after landmark detection by knowing the location of left and right eye's iris, it is possible to align the face.

4.3.2. Color Enhancement

Histogram equalization is another step to prepare the face image. In some images the color quality of pictures are not proper to analyze (like in edge detection). The main function of histogram equalization is the color enhancement and it is based on *probability* *density function (PDF)*. Another effect of this method is that it expands the range of intensity levels in an image. Figure 4-6, represents the effect of applying this method on the face image. Although the source image seems more appealing to eye but the result is more useful when applying feature extraction techniques.

4.4. Color Identification

Cosmetically treated skin can be detected by the means of texture and color analysis, since the main function of makeup is to change color of skin. By using color, many improvements can be obtained on facial skin and facial beauty. Therefore it is crucial to know thoroughly available and common color spaces used in computer science.

The characteristics generally to distinguish color is brightness, hue and saturation. Brightness embodies the achromatic notion of intensity. Hue is an attribute associated with the dominant light waves. Hue represents dominant color as perceived by an observer. So when we call an object red, orange, or yellow we are referring to its hue. Saturation refers to the relative purity or the amount of white light mixed with a hue. The pure spectrum colors are fully saturated. Colors such as pink (red and white) and lavender (violet and white) are less saturated, with the degree of saturation being inversely proportional to the amount of white light added. Hue and saturation taken together are called chromaticity, and, therefore a color may be characterized by its brightness and chromaticity.

The amounts of red, green, and blue needed to form any particular color are called the Tristimulus values and are denoted by X, Y and Z. Associating Tristimulus values with colors is the job of a color space. Y means luminance, Z is quasi-equal to blue stimulation, or the S cone response, and X is a mix (a linear combination) of cone response curves chosen to be nonnegative. Tristimulus coefficients are defined as:

$$x = \frac{X}{X + Y + Z}$$

$$y = \frac{Y}{X+Y+Z}$$

$$z = \frac{Z}{X+Y+Z}$$

4.4.1. Definition of Color

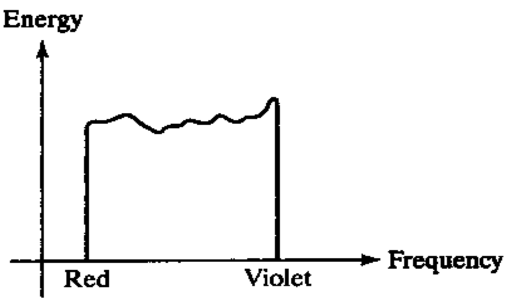


Figure 4-7 Energy Spectrum

Makeup detection in digital images is basically a process that is mostly based on colors. But what is color? Color is not a physical phenomenon. It is a perceptual phenomenon that is related to the spectral characteristics of electro-magnetic radiation in the visible wavelengths striking the retina.

The color of an object depends on the so called *spectral curves* for transparency and reflection of the material and the spectral curves describe how light of different wavelengths is refracted and reflected. Depending on the energy of the wavelengths, various colors may be perceived. Figure 4-7 Energy Spectrumshows the relation between energy and frequency that result in different colors, this distribution is called energy spectrum. This distribution may indicate:

- Dominant wavelength (frequency): the color of the light
- Brightness (luminance): intensity of the light
- Purity (saturation)

These are the characteristics that are used to distinguish colors. Depending on the importance of each of these factors in an application, the appropriate color space would be used. More details about color spaces would be discussed in next chapter.

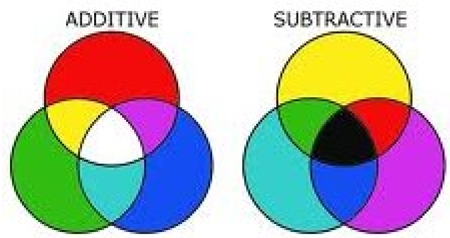


Figure 4-8 Additive and subtractive color mixing

A very useful characteristic of colors is their capability to create new colors by mixing them. The way color mixes together highly depends on the environment under which they mix, for example when colourful lights mix together they would have create different color while painting colors are mixed, the former is mixture of light and the latter is mixture of pigments. Colors can be mixed together in different ways, Figure 4-8:

- additive mixing
- subtractive mixing

Additive mixing of colors generally involves mixing colors of light. In additive mixing of colors there are three primary colors: red, green, and blue. In the absence of color or, when no colors are showing, the result is black. If all three primary colors are showing, the result is white.

Subtractive mixing is done by selectively removing certain colors, for instance with optical filters. The three primary colors in subtractive mixing are yellow, magenta, and cyan. In subtractive mixing of color, the absence of color is white and the presence of all three primary colors is black. In subtractive mixing of colors, the secondary colors are the same as the primary colors from additive mixing, and vice versa.

4.4.2. Color Spaces

Choosing the best color space for many image processing applications is the most fundamental step. In this application, the machine perception of color can vary tremendously depending on the amount (intensity) of the makeup and the lighting conditions on the face. There are many different color spaces that each is useful for certain applications, such as:

- RGB (Red, Green, Blue)
- HSV (hue, saturation, and value)
- HSL (hue, saturation, and lightness)
- CMYK (Cyan, Magenta, Yellow, Key(black))

In the following, RGB and HSV color spaces which are more pertinent to this study will be discussed.

4.4.2.1. RGB Color Space

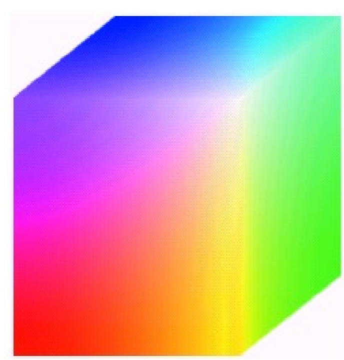


Figure 4-9 RGB Cube

RGB color space is the most common color space used in computer graphics because of its similarity to human eye perception, Figure 4-9. RGB is additive (Figure 4-8 left) and consists of three primary components (Red, Green, and Blue) but complete RGB specification requires a white point chromaticity and gamma-correction curve[1]. In this color space *Pixel Depth* means the number of bits used to represent each pixel in RGB space. Depending on pixel depth we can produce more colors. The full-color image with 8 bit depth for each component (R, G, B) = (8 bits, 8 bits, 8 bits) is 24-bit RGB color image, Figure 4-10.

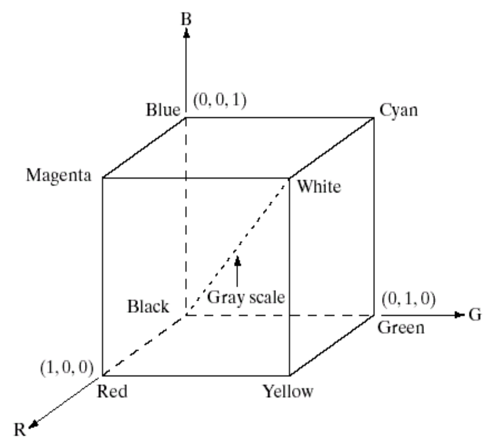


Figure 4-10 RGB Color Cube Model

Simplifying the design and architecture, RGB is a basic model for computer graphics. However RGB is a device-dependent color model so different devices does not produce same color with same RGB. It is a common model for television systems, digital cameras and image scanners.

The disadvantage of this color space is the necessity of equal pixel-depth and display resolution for all three RGB components because of their high correlation, furthermore any adjustment in image requires change in three planes.

[1] The luminance intensity generated by most displays is not a linear function of the applied signal but is proportional to some power (referred to as *gamma*) of the signal voltage. As a result, high intensity ranges are expanded and low intensity ranges are compressed.

4.4.2.2. HSV Color Model

HSV is another useful color space consisting of three components (hue, saturation, value):

- Hue: color attribute
- Saturation: purity of color (white -> 0, primary color -> 1)
- Value: achromatic notion of intensity[1]

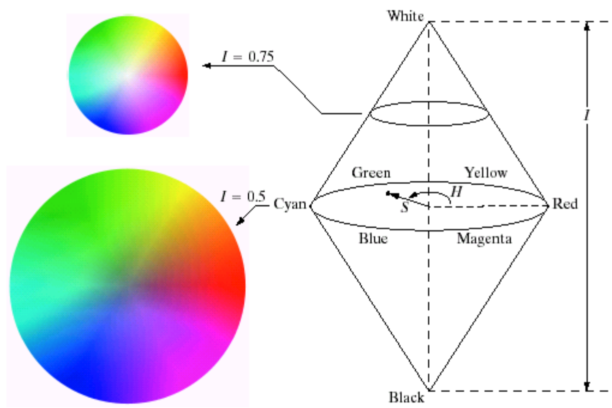


Figure 4-11 HSV Color Model

HSV is cylindrical geometry. In this model Hue which its angular dimension, starts at the red primary at 0°, passing through the green primary at 120° and the blue primary at 240°, and then wrapping back to red at 360°, Figure 4-11. Saturation is the depth or purity of the color and is measured as a radial distance from the central axis with value between 0 at the center to 1 at the outer surface. In order to create different colors, the pure colors should be mixed with tint (white) and the shade (black). The value of intensity specifies the particular gray shade to which this transformation converges. When the saturation is near 0 all the colors even with the different hues appear the same.

Figure 4-12, represents the result of converting the RGB image to HSI color space. The RGB image consists of primary and secondary RGB colors. HSV and HSB are another alternative of HSI color space. Both the HSL and HSV are cylindrical geometrics with hue ranging from 0° to 360°.

[1] Achromatic notion is what viewers see on black and white TV

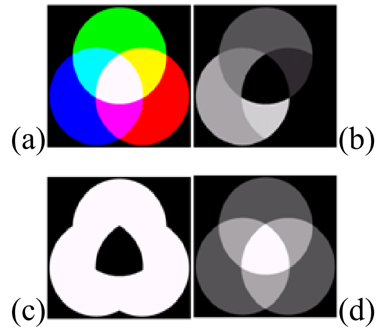


**Figure 4-12 The different representation of colors:
(a) RGB image, (b) hue;
(c): saturation and (d) intensity [52]**

Detecting human skin is one application of this color space. For detecting skin according the color pixels are filtered according to hue values ranging between 6 and 38. The skin in channel H is characterized by values between 0 and 50, in the channel S from 0.23 to 0.68 for Asian and Caucasian ethnics.

4.4.2.3. The CMY and CMYK color models

Cyan, magenta and yellow are the secondary colors of light and the primary colors of pigments. For example when a surface coated with cyan pigment is illuminated with white light; no red light is reflected from the surface. That is cyan subtracts red light from reflected white light, which itself is composed of equal amounts of red, green, and blue light.

Very simple conversion between CMY and RGB:

$$[CMY] = [1\ 1\ 1] - [RGB]$$

Equal amounts of the pigment primaries, cyan, magenta and yellow should produce black. Since this color model is for printing purposes and black is the predominant color in printing, a new color black is also added to this model which becomes: CMYK, which is highly device dependent and the color printed relies on the paper and ink for the printing device. CMY (K) is a subtractive model (Figure 4-8 right).

Conversion from CMY to CMYK is [53]:

$$Black = minimum(Cyan, Magenta, Yellow)$$

$$Cyan = (Cyan - Black)/(1 - Black)$$

$$Magenta = (Magenta - Black)/(1 - Black)$$

$$Yellow = (Yellow - Black)/(1 - Black)$$

4.4.2.4. Computing HSV from RGB

The algorithm below is used to compute HSV from RGB according to Intel manual [54]:

```
// Value:
V = max(R,G,B);
// Saturation:
temp = min(R,G,B);
if V = 0 then // achromatics case
      S = 0// H = 0
else // chromatics case
      S = (V - temp)/V
// Hue:
Cr = (V - R) / (V - temp)
Cg = (V - G) / (V - temp)
Cb = (V - B) / (V - temp)
if R = V
       H = Cb - Cg
if G = V
            H = 2 + Cr - Cb
if B = V then H = 4 + Cg - Cr
H = 60*H
if H < 0 then H = H + 360
```

4.4.3. Color features

Makeup detection technique can be categorized in to two main approaches: pixel-based and region-based. In pixel-based approaches, the color of pixel is considered as feature; while in region-based approaches, classification is based on spatial information of pixels (such as texture). Both techniques are used in this research to get good result. Pixel-based information is required like the Hue of one pixel of the skin as well as the regional information of that area. In this section the techniques used to extract features from pixel colors will be discussed.

4.4.3.1. Color histogram

Histograms are great statistical representation of intensity level distributions. Distance between histograms of images is a good measure for comparing similarities between the two distributions.

The histogram of a grayscale image with intensities in the range $[0, L-1]$ is $h(r_k) = n_k$ which $h(r_k)$ is the histogram value for the grey level r_k and n_k is the number of pixels in the image that have gray level r_k. For grayscale images one and for the RGB images three histogram can be obtained.

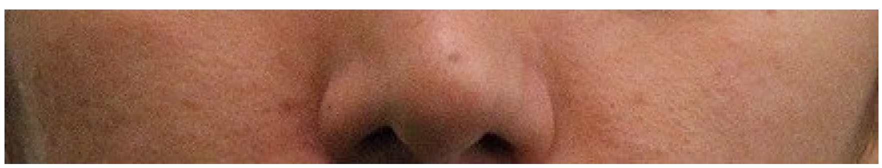


Figure 4-13 Sample of skin patch

In this study to get the range of skin colors of each individual a sample of face image which starts under the eyes and ends above the lips, is taken. From this patch many statistical information about facial skin of the individual can be retrieved. Histogram is one useful tool to get such information.

Figure 4-13 is a sample of the individual skin and Figure 4-14 is the histogram of R component of the RGB image. Since R stands for red in RGB color space, it contains the red color information of the image. We can get the number of pixels with a specific color like red (because each color consists of three different components) from the calculated histogram. Therefore any color can contain small amount of red. There exists another color space called HSV, discussed in 4.4, which specifies the color itself when the information about the intensity and the brightness is not important.

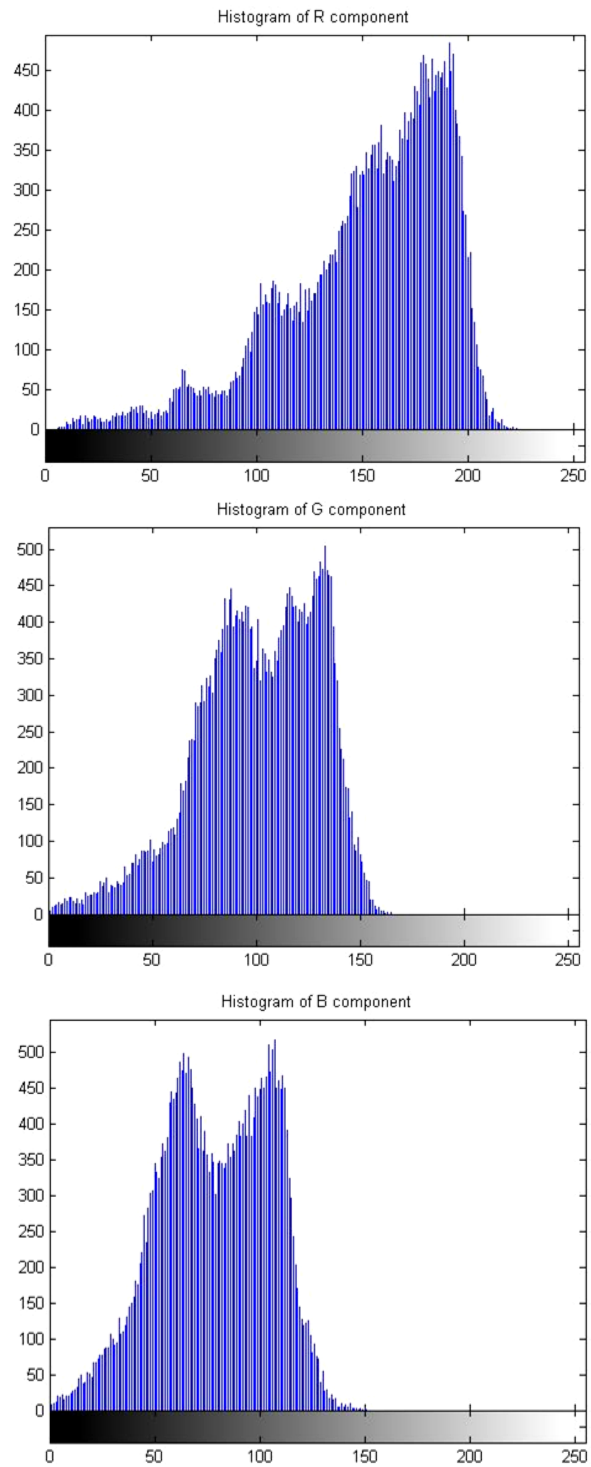


Figure 4-14 Histogram of R, G and B component of an image

The histogram for hue component of Figure 4-13 is shown in Figure 4-15 describes that the source image's hues mostly range [0-17] with low number of dark pixels.

HSV color model is a very useful model in makeup detection since sometimes makeup has colors other than skin tone, therefore when different colors like blue or green are applied it would be easily detected.

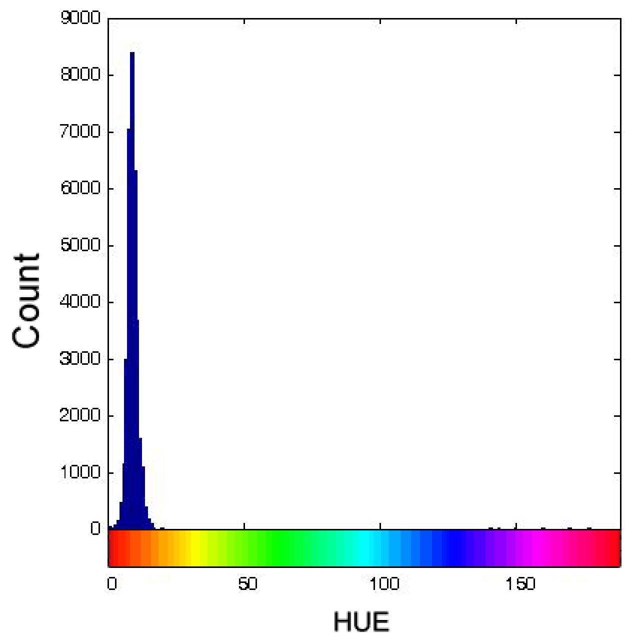


Figure 4-15 Histogram of hue component in HSV model

Another advantage of using histogram is that by defining the threshold on the count, it is possible to eliminate hues that have very small number comparing to the size of image. For example in Figure 4-13 which has the size 77x438 that is over 33700 pixels, hues with total number of 20 pixels shouldn't be counted as valid hues for this skin. These colors might be result of shadows or discoloration of skin.

4.4.3.2. Color distance

Color distance is another useful feature in makeup detection technique. Since colors are considered as vector, it is possible to calculate their distances. In 3-D space, the distance between two colors C_1 and C_2 is calculate by $\|C_1 - C_2\|$, which could be calculated with Euclidean distance.

In RGB color model it is calculated as follows:

$$\|C_1 - C_2\| = \sqrt{(C_{1,R} - C_{2,R})^2 + (C_{1,G} - C_{2,G})^2 + (C_{1,B} - C_{2,B})^2}$$

In RGB color space how is it possible to say which colors are close to a chosen color? One answer is to set a similarity parameter and calculate Euclidean distance for other colors and any color which has a distance less than or equal to similarity would be close to our color. This would end up to a sphere in RGB cube around that color. What happens from a perceptual view is that, for example, if the person wants all the colors closer to Royal Blue which is those with bluish point, this will not happen in this calculation. However, it is possible to put some limitations but not a mathematical solution [55].

HSV provides a better solution to this problem. In HSV model, following steps are required to find the closest colors.

- Calculate the hue of chosen color if it is in RGB space
- Pick a threshold for that hue
- Cut a pie slice from the HSV cone
- Limit the value (high of HSV cone) in order to eliminate too dark and too bright colors

With this method all the colors close to blue would be chosen and colors close to white and black are far from the Royal Blue is deleted. Therefore all the limitations of color, saturation and value are applied.

In this research the average hue obtained from the sample patch is the scale to compare other colors with. For eye-shadow and lipstick it is a good feature too analyse to which extent the colors are different from the normal skin with no makeup. The sum of all the distances from the average hue is a good representative of overall color variation.

4.4.3.3. Non-skin colors

In makeup detection, the main question is how to differentiate skin colors with non-skin colors? The answer to this question highly depends on the lighting conditions, head orientation and gesture of the person.

The proposed method to find the invalid skin colors is first to find the most possibilities of the individual's skin color with a sample of her skin (Figure 4-13) and then by converting the color model to HSV color space all the possible combination of hue, saturation and value should be calculated. For this step the image histogram is a good approach since by putting threshold on the number of found pixel for each hue or saturation the low possibilities would be eliminated. This will result in a 3-D area in HSV cone. In final step by defining a bounding box on an image and examining all the pixels within its area to see whether it's h, s and v components are valid values. Areas with higher number of invalid hue ratios are considered as makeup target for that particular face.

This approach leads to some misrecognition of pixels, since color is the base of this technique and any modification to color can lead to wrong recognition.

Figure 4-16 Effect of shadow on skin color:
Left) One spot light and Right) Indoor light and one spot light

Shadow on face is one of the main problems on face analysis applications. Shadow or lack of light causes loss of information under the area of shadow, like color, edges. Figure 4-16 represents two images from the makeup database the effect of shadow on the face skin color. In the right image the spot light has brighten the right part of the face but it does not have much effect on hue (color): 23-25. However in the left image the shadow has changed the hue tremendously: 8-17. Recently many scientists have been working on restoration of images under shadow. In 2009[56], Tuan *et al*, remove the shadows by color segmentation and morphological processing. In this research photos with extreme shadow are not considered for makeup detection.

Noise and blink are two other effective issues in false makeup detection. The first problem is for landmark detection, since most approaches discussed in this research are based on edges and colors (or profile which is discussed in section 4.2.8) they fail to give good result. Figure 4-17 is an example of the makeup database, which the person has almost closed eyes. For this image the application was not able to locate invalid skin colors.

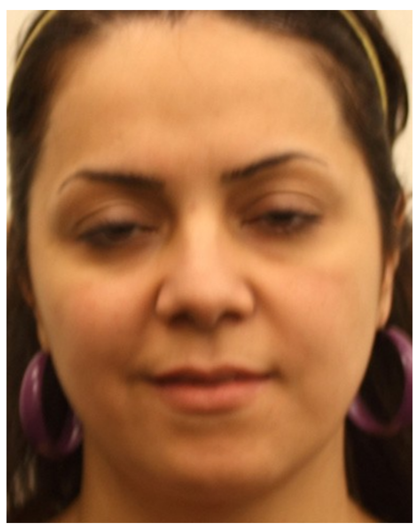


Figure 4-17 Example of closed eyes in an image

4.5. Texture Analysis

Although makeup changes the skin color with cosmetics, it is not the only effect on face image. Makeup changes the skin texture as well. Smoothing the skin, foundation covers the dots and pimple therefore presenting healthy skin. What happens is that from the image processing point of view it removes the edges on the skin. On the contrary cosmetics like eye-shadow causes the eye look more prominent or smaller by means of dark or bright colors. Therefore eye-shadow creates trivial or major edges on digital image.

Statistical information of these edges is a good feature for makeup detection.It is also possible to study the wrinkle density and wrinkle depth to define how much foundation may be helpful to cover the wrinkles. Wrinkle density and depth could be calculated by following formulas:

4.5.1. **Edge Density**

The density of edge in area A is defined:

$$Dn_A = \frac{W_A}{P_A}$$

where W_A stands for the set of all edges pixels in area A, PA is the set of all pixels in area A. The value of Dn_A, A is between zero and one. The more the edges are, the closer to one the value of Dn_A is [57]. For finding the edges of the image Sobel edge detector is used. Figure 4-18 represents the result of Sobel edge detector on face image.

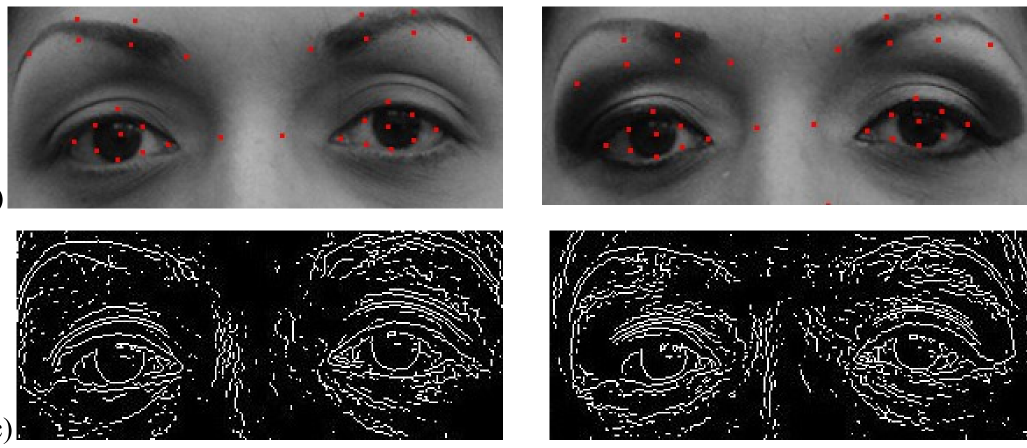
4.5.2. Edge Depth

The depth of edge in area A is defined as:

$$Dp_A = \frac{1}{\alpha|W_A|} \sum_{x,y \in W_A} M(f(x,y))$$

where $M(f(x, y))$ stands for the Sobel edge magnitude (the simpler absolute values are used in this implementation) of wrinkle pixel with coordinates (x, y) in W_A, and $|\cdot|$ represents the number of the elements in the set. In order to avoid the saturation problem during neural network training, the depth of wrinkles is divided by a constant α (255, in this study). The deeper the wrinkles are, the larger the value of Dp_A is [57].

It is essential to know that cosmetics add to the density of wrinkles to some extent:



(a) (b)

(c) (d)

Figure 4-18 Results of Sobel edge detector on face, before and after makeup: a)the image without makeup; b) the image with makeup c) Result of Sobel on image (a) and d) Result of Sobel on image (b)

4.5.3. Gabor Wavelet

A Gabor filter is a filter used effectively in face recognition and image processing. It is a filter that can filter for a specific angle and frequency and it's a combination of a cosine and a normal distribution, therefore it is a powerful tool to generate features.

Gabor filter works as a band-pass filter for the local spatial frequency distribution, achieving an optimal resolution in both spatial and frequency domains. The 2D Gabor filter $\psi_{f,\theta}(x, y)$ can be represented as a complex sinusoidal signal modulated by a Gaussian kernel function as follows

The Gabor Wavelet is given as the product of a Gaussian low-pass filter with a exponential [58]:

$$\psi_{f,\theta}(x, y) = g'(x, y)\exp\left(j\left(w_x x + w_y y\right)\right)$$

where:

$$g'(x, y) = \frac{1}{\lambda\sigma^2} g\left(\frac{x'}{\lambda\sigma}, \frac{y'}{\sigma}\right),$$

$$g(x, y) = \frac{1}{2\pi} exp\left(-\frac{x^2 + y^2}{2}\right)$$

In this formula $g(x, y)$ is the Gaussian filter and $g'(x, y)$ the scaled (by parameter σ) and rotated (by parameter θ) version of that. The directionality of the filter which here is the aspect ratio of the filter is defined by λ. Here x' and y' are defined as:

$$x' = \mathrm{x}\cos\theta + y\sin\theta$$

$$y' = -x\sin\theta + \mathrm{y}\cos\theta$$

By varying the three parameters σ, θ and λ this formula generates different filter with different orientation and frequencies. Filter's center circular frequency is used to calculate θ:

$$w = \sqrt{{w_x}^2 + {w_y}^2}, \qquad \theta = \tan^{-1}\frac{w_x}{w_y}$$

In this chapter the steps to extract features from the images in order to use for classifier were discussed. Pre-processing was necessary to get a better result. Color enhancement helps to retrieve the edges more effectively and the face alignment is for accurate extraction of face features. Then for each part of the face the appropriate features will be extracted. Color is very important in studying the makeup on face, since for eye-shadow and lipstick are the main targets is to give a nice and smooth color to the skin. Therefore the most suitable color space is chosen for this purpose. The strength of this color space is that it distinguishes the pure color from the shade and brightness.

In the next chapter the implementation of the methods described here will be discussed. Then the features and the result of the three subsystems for makeup detection of eyes, lips and skin will be studied separately.

Chapter 5

5. Implementation and Results

This chapter describes the implementation and results obtained by using the features described in the previous chapter. In this chapter, first the result of landmark detection with Active Shape Model (ASM) will be discussed then the problems and improvements for makeup detection on eyes, lips and skin will be discussed. Support Vector Machine (SVM) is the classifier used in this research to classify the images into a binary category: with and without makeup. The proposed system is mainly composed of three phases:

1. landmark detection
2. feature extraction
3. makeup classification

Since makeup can be applied on different parts of the face, meaning having makeup on one part does not necessary mean its existence on other parts of the face; therefore, we do not study all the features of the face all together. People might have only eye-makeup or just skin foundation. Therefore, we break down the process to some partial makeup detection systems.

(a)  (b)

Figure 5-1 Land mark detection:
a) Face with landmarks and b) Face with landmarks and their numbers

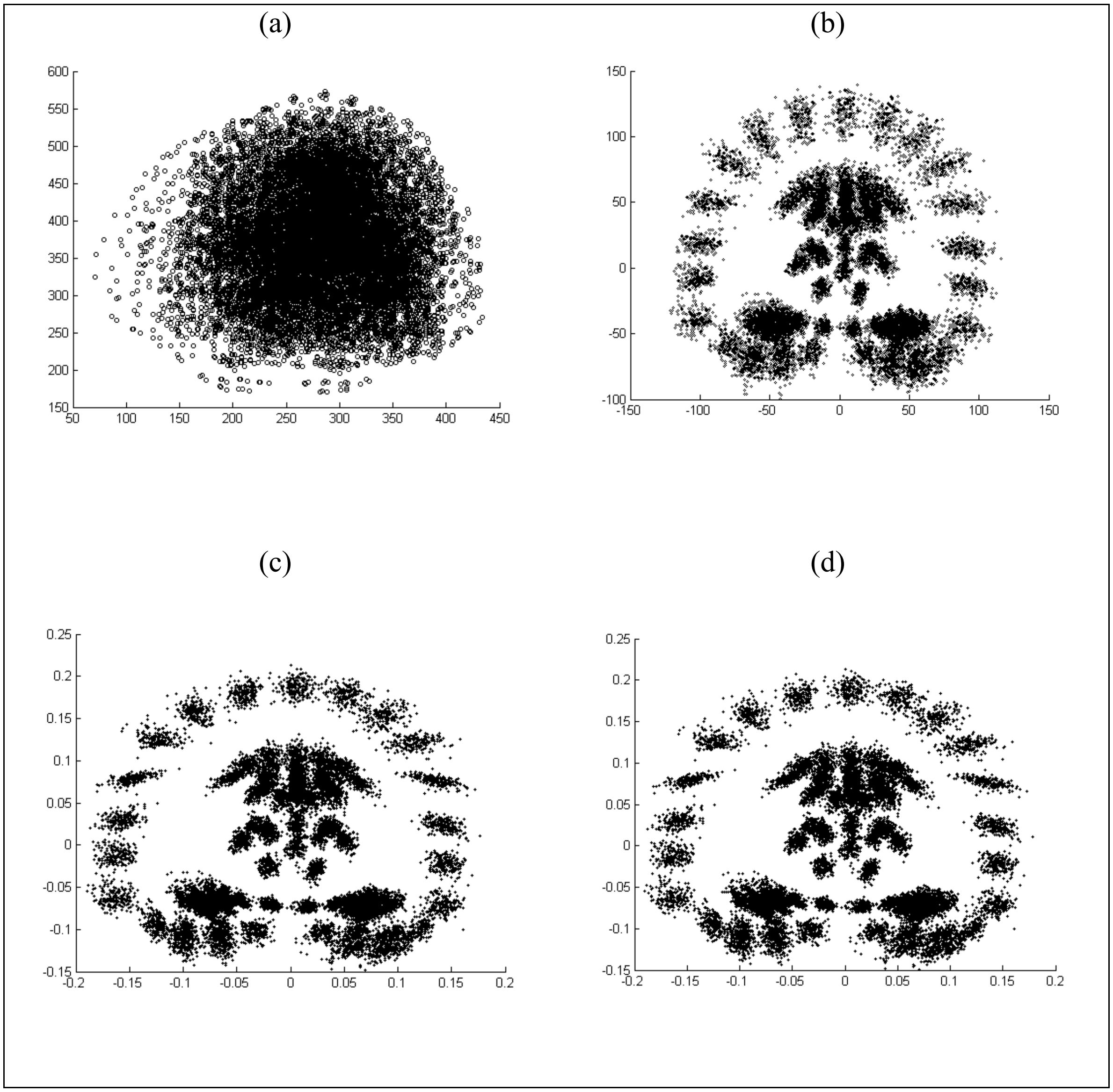
The potential locations for makeup are:

1- Eyelids
2- Lips
3- Face skin

and the common cosmetics used for beauty are:

1. Face foundation
2. Mascara
3. Eye-liner
4. Eye-shadow
5. Lipstick
6. Lip-liner

Table 5-1 Alignment of landmarks: a) the initial data without any modification; b) the translated images to the center of gravity; c) shapes rotated and scaled to unit size and d) training set aligned to the second mean shape



Moreover there are various makeup types ranging from very fade and hidden type to very intense type. Lighting conditions and the orientation of the head in the photos are very important. In this study the focus is on the frontal faces with normal lighting.

5.1. Landmark detection subsystem

Detecting landmark was a challenging part of this research. Although the diversity of landmark detection techniques is high, the best method for this application is Active Shape Models (ASM). Figure 5-1 displays the result of landmark detection with landmark numbers. These numbers are used a lot in this research to retrieve face features from the image.

For landmark detection, the MUCT which is one of the good face databases is used. This database contains frontal face images with no glasses and defects. 3755 faces with 76 landmarks are provided with this db, therefore there is not any need to place them manually. For the implementation, the Matlab software is used because of its practical mathematic functions.

The MUCT database consists of 3755 faces with 76 manual landmarks. The database was created to provide more diversity of lighting, age, and ethnicity than available landmarked 2D face databases.

For detecting landmarks using PCA, first it is necessary to prepare data for analyzing this step which is called alignment. In the following figures the step by step result is shown in Table 5-1.

In the training phase, finding the shape parameters is important because later in testing they are required for finding new shapes.

The main concept in the PCA algorithm which consists of the following step is:

1. Initialize the shape parameters, b, to zero.
2. Generate the model point positions using $x = \bar{x} + Pb$
3. Find the pose parameters $T(X_t, Y_t, s, \theta)$ which best align the model points
4. Project Y into the model co-ordinate frame by inverting the transformation T

$$y = T^{-1}_{Xt,Yt,s,\Theta}(Y)$$

5. Project y into the tangent plane to $\bar{x}$ by scaling

$$Y' = y / (y.\bar{x})$$

6. update the model parameters to match to y’

$$b = P^T(y' - \bar{x})$$

7. If not converged, return to step 2

Table 5-2 shows some example shapes from the training set by varying three face model shape parameters in turn between +- 3 of parameter s.

From the training phase 152 eigenvalues are obtained but since the figure shows the first 36 values are higher than the rest so those first 36 are chosen, the rest gives error.

ASM Search Algorithm for Faces (Testing Phase):

1. Examine a region of the image around each point X_i to find the best nearby match for the point X'_I (this is done profile matching).
2. Update the parameters (X_t, Y_t, s, θ, b) to best fit the new found points X.
3. Apply constraints to the parameters b, to ensure that the shape generated is similar to those in the original training set (e.g. limit so $|bi| < 3\sqrt{\lambda i}$).
4. Repeat until convergence.

Table 5-2 Different shape models obtained in the training phase

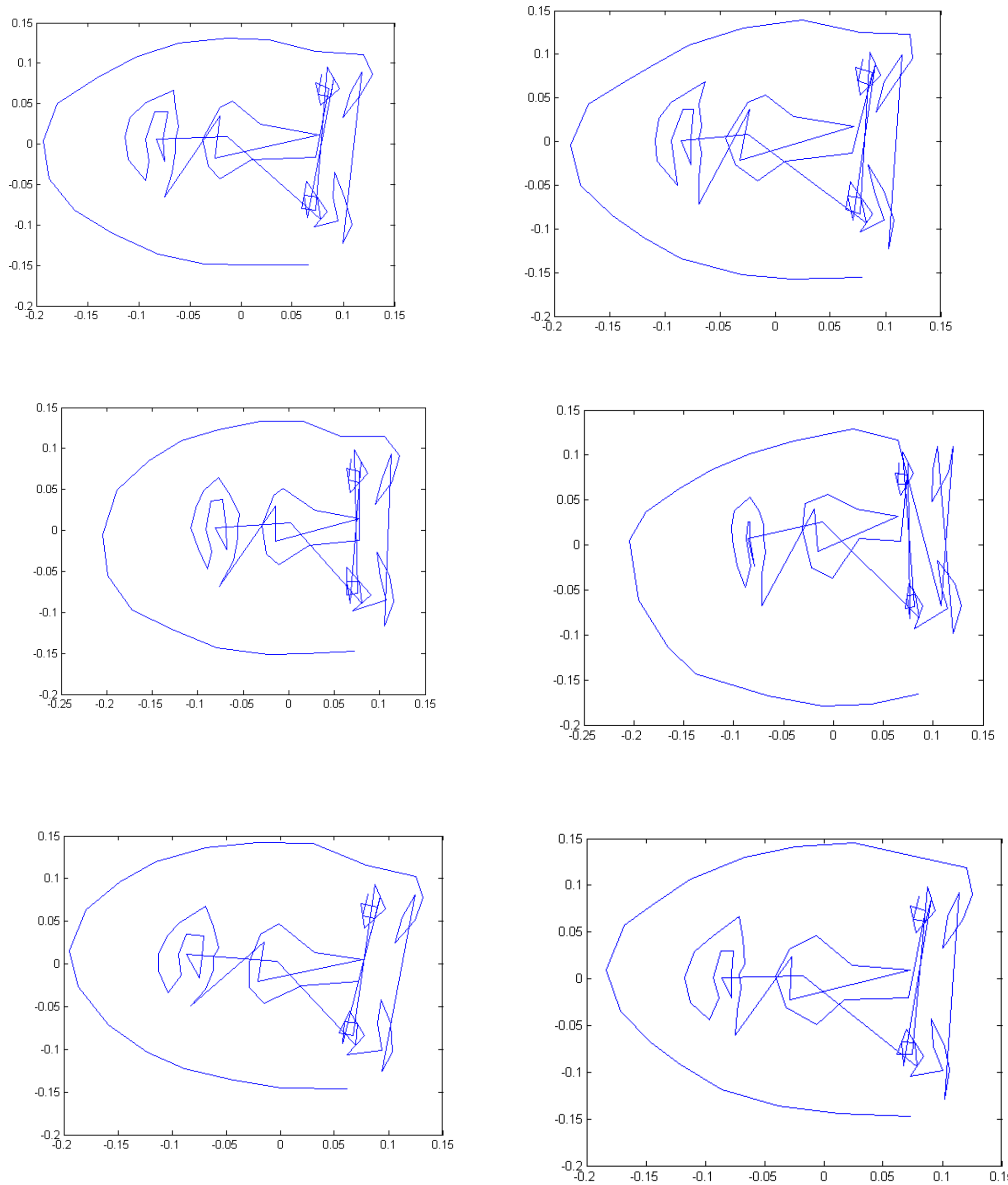


Figure 5-2, represents a sample for starting the search algorithm. After each iteration, the positions of landmarks improve. The preliminary position is critical in obtaining a good result. Otherwise after a few iterations the search algorithm stops and outputs a wrong result.

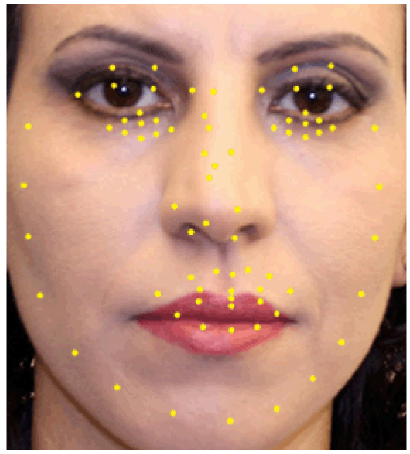


Figure 5-2 Starting Search

In most cases ASM returns very good result but if the face has a bit of rotation or bad lighting the result might not be promising, therefore a revision is suggested to alter the landmark locations.

Since the new makeup database contains images with a heavy makeup and the profiles are different in face with makeup, the extended model of ASM should be used (defined by S. Milborrow) [48].

Figure 5-3 Result of landmark detection on images with and without makeup

5.2. Eye-shadow detection subsystem

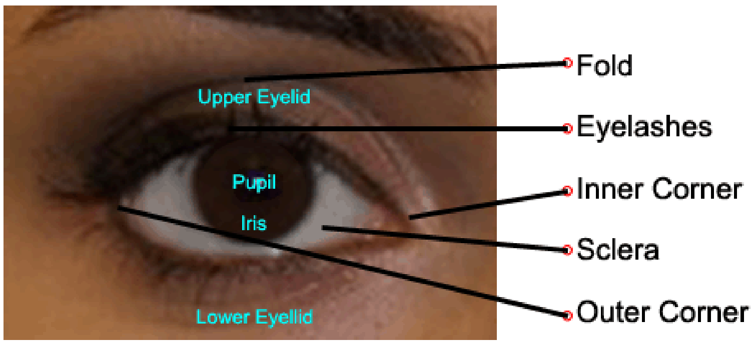


Figure 5-4 Eye's Features

The eye is the most prominent feature in face, which is important from different aspects such as beauty and functionality. Detecting eye makeup can be very complicated because of the eyes' location on the face, which is deeper comparing to other face elements such as nose and forehead. This causes some shadows on the eyes. The nose may lay shadow on the eyes depending on the light direction as well. Figure 5-4 displays the eye's features and their corresponding names. The dark shadows appear on the upper and lower eyelids are because of the eye-shadows applied on eyelids. The bright color around the inner corner is caused by the light color eye-shadow on it. The eye-lashes look darker and thicker in this image because of the mascara applied on them.

5.2.1. Feature Selection

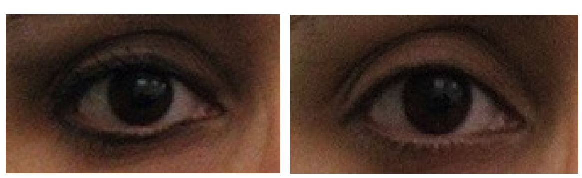
(a)  (b)

Figure 5-5 Two samples of eye area:
(a) with makeup and (b) without makeup

For detecting eye-shadow, the first step is to determine the area which might have the eye-shadow around the eyes. To this purpose all the probable areas must be examined, which is the area below the eyebrow and a bit under the eyes, Figure 5-5. As seen in Figure 5-5 there is not much difference between (a) and (b) when the image is dark. In this section the techniques to enhance the image quality and the appropriate features used will be discussed.

5.2.1.1. Color adjustment

Before any process on the eyes, primarily the color of the whole image should be adjusted. This is necessary both for sampling the skin color and the eye-shadow detection. The contrast adjustment helps to locate the eye-shadow by adding more difference to the colors of eye-shadow and the skin. For this purpose Histogram Equalization, described in 4.3.2, is used, see Figure 5-6.

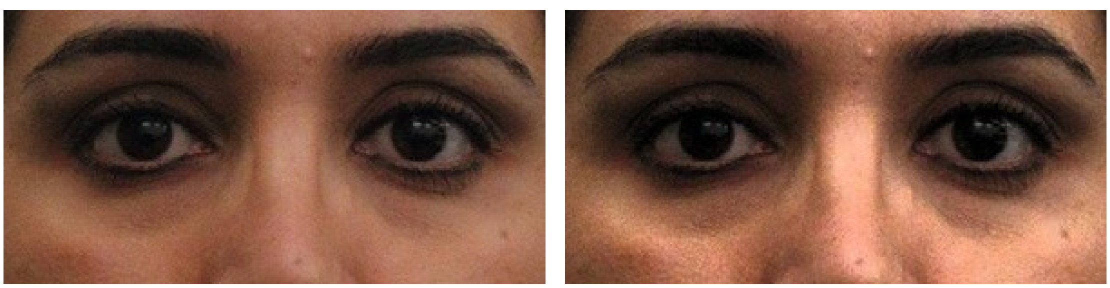


Figure 5-6 histogram equalization on eyes:
Left) the source image and Right) the result of applying the histogram equalization

5.2.1.2. Invalid eye skin color ratio

The most obvious feature about the eye-shadow is the color, the feature that makes it special among other cosmetics. There are various colors for eye-shadow, some are fading and some are very sparkly, ranging from very bright colors to very dark shades like black.

Consequently, color is an important feature to identify eye-shadow. But how is it possible to distinguish the eye-lid color and eye-shadow? To answer this question a patch of face skin of the same person which has also some shadows on it will be used to get the information about this particular person's skin, Figure 5-7. This sample is a good indicator or possible hues of normal skin which may have also small amount of shadow on it like the areas of nostrils. This should be carefully chosen, if for example the sample contains some part of the lip then it cannot recognise if the lip color is normal or it is lipstick.

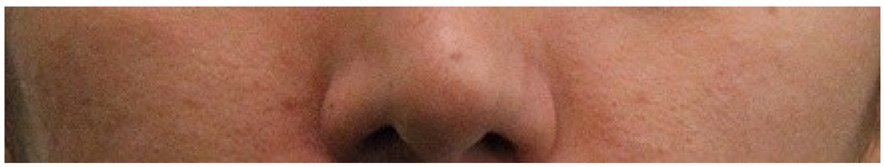


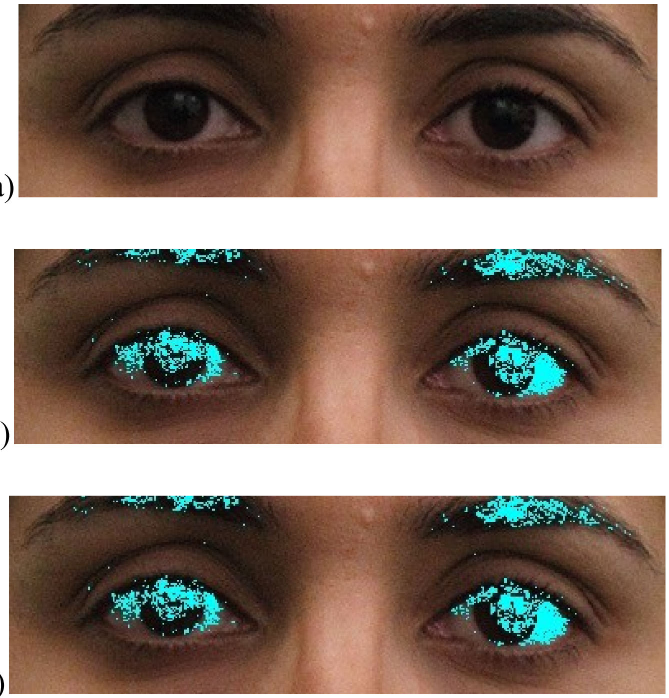
Figure 5-7 Skin Sample

This sample gives the possible hues and saturations for the skin of this particular person. The sample's histogram should be calculated, and then the hues and saturations that have zero quantity are not valid skin color for this person. Setting a threshold is helpful in some applications to eliminate the invalid pixels.

If max_{hue} denotes the maximum number of hue histogram for all the bins, by defining the scale factor k, the *thresholding function* is:

$$hue\_threshold = max_{hue} * 1 / k$$

In Figure 5-8, the result of applying this technique on Figure 5-8-a, is shown, the blue dot means the pixel has non skin color. As it can be seen in Figure 5-8-b the eye-lid is detected well but in some areas like eyebrow we have some misdetection which for our purpose is not a big issue since we cover the entire eye and eyebrow. In Figure 5-8-c, we see that threshold was not a great help.



a)

b)

c)

Figure 5-8- Classifying skin-color and non skin-color on image without makeup: a) original image; b) detecting non-skin color and c) detecting non skin-color with threshold

Figure 5-9, shows the result of the technique on the same person's photo but with makeup. As it is shown in Figure 5-9-b the eye-liner is detected properly but to identify the eye-shadow the threshold must be modified to get a better result. Since in every photo the colors and illumination are different, the threshold must give good result in all photos. Figure 5-9-c shows that the threshold did not help much in recognition. It can be seen that the eye-liner is properly detected but since the eye-shadow is not that obvious, it can not detect it very well. The main reason here is that the eye-shadow's color is dark brown so the base color is very similar to the face skin color. For such cases we need another feature to improve the results.

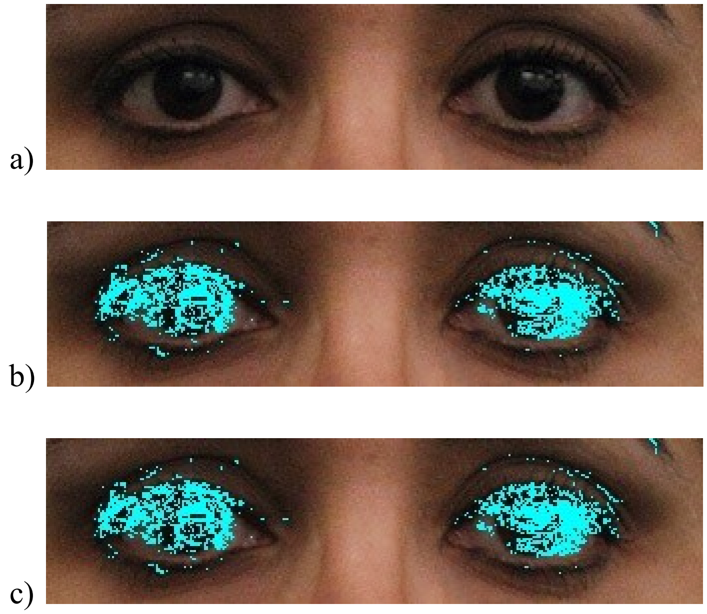


**Figure 5-9 Classifying skin-color and non skin-color on image:
a) original image; b) Detecting non-skin color and
c) detecting non skin-color with threshold**

Figure 5-10 is another example of the result of applying the method. Here the base color used for eye-shadow is blue; therefore it gives a very good result. Finally the invalid number of pixel colors for the eyes is obtained by:

$$Ratio\ of\ invalid\ number\ of\ pixels = \frac{total\ number\ of\ blue\ pixels}{image\ width * image\ height}$$

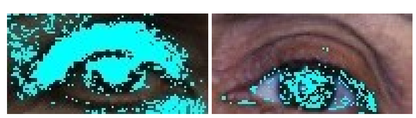


Figure 5-10 Detecting non-skin color

To improve the result of extracting the number of invalid pixels, the non-skin area of the eyes (iris, and sclera) should be covered.

5.2.1.3. Eye's sclera detection

In order to improve the eye makeup detection, adding more features can help to some extent. But one issue that was perceived while counting the eye's invalid number of pixels is that although covering the eye with a rhombus shape helped a lot, it did not cover inside the eyes specially the white pixels of sclera. These incorrectly chosen pixels lead to wrong classification, since in eyes with and without makeup we have white pixels of sclera.

Because only the information about the makeup on eye's skin is important, inside the eyes should not be analyzed and it should be masked. This section discusses the method to cover inside of eye. When detecting the eye-makeup, one of the important steps is to locate the eye's area [59]. Unfortunately the ASM method does not find the precise location of eyes; therefore a supplementary method is necessary to alter the landmark locations.

Iris is the most important feature in eyes. Having a ring shape makes it easier to detect; however, finding the location of iris can be difficult. The other two important features are upper and lower eyelids. According to the amount of the eyes opening and curvature, the shape of the eyes can vary. Eye corner is the meeting place of two eyelids. Inner corner refers to the corner close to the nose and outer corner is the one closer to the ear, Figure 5-4. Two possible solutions are discussed below.

Sampling Scleras

One method to find the eye landmarks is to create a database of eye's sclera and then find the possible color values of sclera. Usually this gives a good estimation of the eye sclera and consequently the eye corners, this is only estimation; moreover to get a more accurate result, complicated algorithms must be applied.

Finding sclera with samples of sclera did not help, for some images it was so good but for some not at all.

Contour Detection

Contouring is a good technique to find the border of an object, which is the result of image segmentation. In this research it is used to get the border of sclera in eyes. Since sclera has almost a solid color it is possible to define the area of sclera, Figure 5-11.

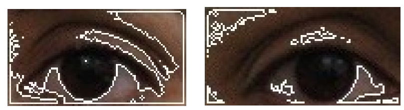


Figure 5-11 Two samples from the result of contouring

In order to obtain a better result for contouring the eye's sclera, the following steps are performed:

1. Cover the eye area by using the available landmarks with a color close too sclera's color, Figure 5-12-c
2. Apply contour detection with threshold value 95 (this value is obtained experimentally), Figure 5-12-d
3. Fill inside the contours, Figure 5-12-e

The bright color used in step 1 helps the next step to get a better result on next step and the neutral color used in final step (3) is used to mask the image while counting the invalid pixel colors. These white pixels will not be included when counting the invalid pixel colors.

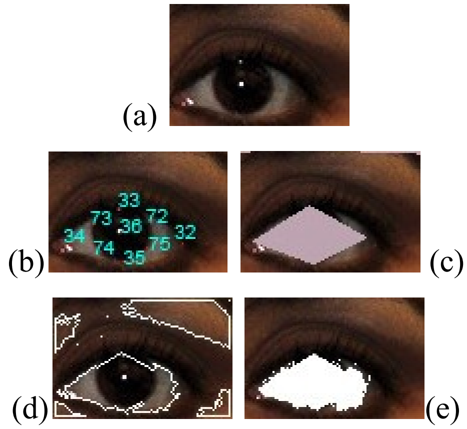


Figure 5-12 contour detection for sclera:
(a) source image
b) landmarks detected on image (a); c) image (a) covered by landmarks;
d) founded contours on (c) and e) contour filled on image (d)

5.2.1.4. Edge density and edge depth

Other features which are used in the research are edge density and edge depth. Applying cosmetics on the face introduces some small edges because of the shiny effect they have. These edges give information about the characteristics of the texture. Figure 5-13 shows the result of applying edge detector on a face. As it can be seen in Figure 5-13-d we have more edges around the eyes compared to Figure 5-13-b. As such used Sobel edge detector is used. The Sobel edge magnitude, approximating gradient magnitudes, is used to judge the degree of edges, since makeup has changed the intensity and some even form clear lines. If a pixel belongs to makeup, then its Sobel edge magnitude is larger. A thresholding is necessary to eliminate non makeup pixels.

In the next step, the effects of applying threshold on the edges are verified. The result obtained from several samples and images is that the threshold 40-50 gives the better estimation but still the depth does not change much. Probably the reason is that the shadow is applied gradually, see **Error! Not a valid bookmark self-reference.**. By doing two special modifications the result will improve to some extent:

1. Add contrast and brightness

2. Set threshold to 60- 90

Table 5-3 explains that the density ratio and depth ratio do not produce much difference with the same threshold in images with or without makeup. To solve this issue it is necessary to add contrast to the eye image.

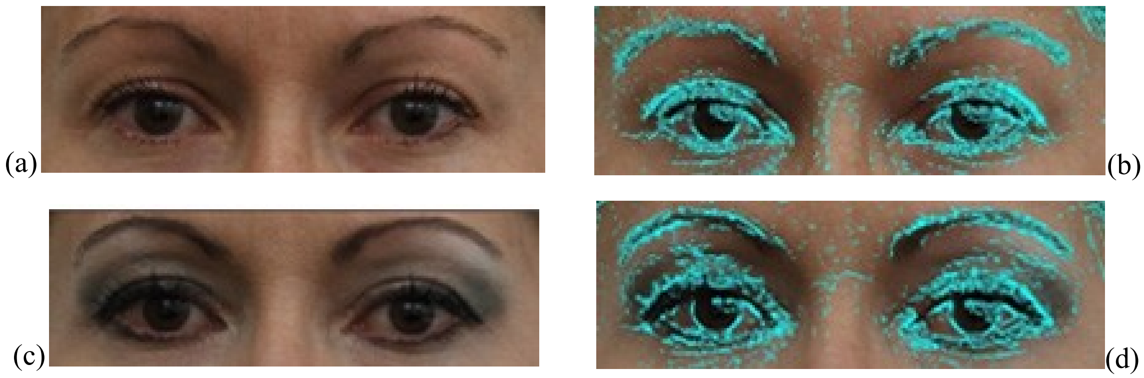
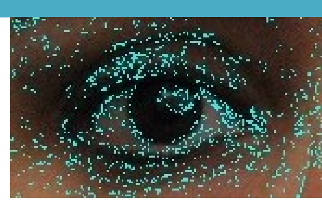


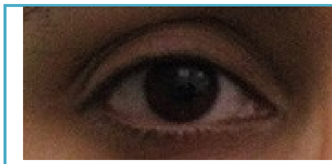
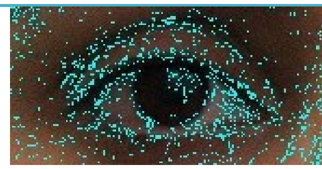
Figure 5-13 Edge density on face:
a) photo with no makeup; b) applying edge detector on image (a);
c) photo with makeup and d) applying edge detector on image (c)

The result obtained from several samples and images is that the threshold 40-50 gives the better estimation but still the depth does not change much. Probably the reason is that the shadow is applied gradually, see **Error! Not a valid bookmark self-reference.**. By doing two special modifications the result will improve to some extent:

3. Add contrast and brightness
4. Set threshold to 60- 90

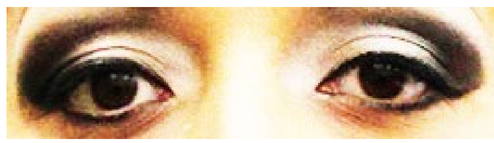
Table 5-3 Comparing edge depth and edge desnity obtained from Sobel edge detector

Soure Image	Result of Sobel	Density	Depth	Thresh.
		0.087	0.25	40-50

		0.090	0.27	40-50

This creates deeper edges and deletes the very minor differences. Moreover mostly focuses on the changes of the color and brightness.

Figure 5-14 displays the result of the Sobel Edge detection on contrasted image with threshold range [60, 90]. The density and depth obtained were 0.34 and 0.40 respectfully.

a) 

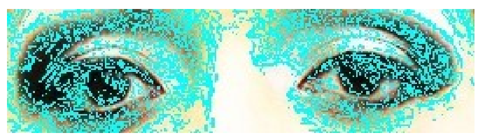
b) 

Figure 5-14 Applying Sobel Edge detection on contrasted image:
a) the source and b) the result of applying Sobel edge detector on (a)

Figure 5-15 shows the result of Sobel Edge Detector on retouched images. This explains the efficiency of this method on retouched image as well.

Sample 1:

Sample 2:

Figure 5-15 Edge density:
left) Original image; middle) Contrast added to original image and
right) result of edge detector on middle image

5.2.2. Classification

In this research, an SVM (Support Vector Machine) classifier is used as a classifier. The rate of database division for train and test was 60% for train and 40% for test. The features used in this classification are:

1. Right eye invalid colors ratios
2. Left eye invalid colors ratios
3. Right edge density
4. Left edge density
5. Right edge depth
6. Left edge depth
7. Right eye color distance
8. Left eye color distance

Since it is supposed that the amount of makeup is usually the same for the left and the right eye, the statistical values for both eyes are considered. The threshold value for edge detection was set to the range [0, 60].

5.2.3. Results

The result of SVM classifier with gamma = 0.5 for features described in previous section is shown in Table 5-4:

Table 5-4 Results of Eye-shadow detection with SVM classifier

	No. in testing	Correct Estimate	Wrong Estimate
With makeup	16	15 (93.7%)	1 (6%)
Without makeup	16	13 (81%)	3 (19%)

This result is for a classifier with 102 frontal face images, which had 70 images for training and 32 images for testing. The images are spread randomly for training and testing. Half of the testing images were with makeup and the other half without makeup.

The recognition rate for the eye-shadow recognition rate was 90.625 %, meaning it was able to estimate 29 out of 32 eye images correctly.

Figure 5-16 displays an example of a bad image that could lead to a wrong result. Problems with closed eyes are related to finding the eye landmarks improperly and also the hues and saturations of eye-lid will change dramatically; moreover sometimes it produces extra edges that increase the edge density and edge depth of the eye features.

Figure 5-16 Two samples of closed eyes from the database that cause wrong detection

Testing several subsets of features is so helpful for finding the best subsets that produce the best results. Table 5-5 shows the results of using different features. Having all the features described in previous section except the color distance produced 71.87% accuracy on the same training and testing images. However by using the color distance feature for only one eye 78.125% accuracy was achieved. By removing the invalid color ratios the accuracy is 68.75%.

Table 5-5 Result of eliminating features in eye-shadow detection

Eliminated Feature	Result
Invalid colors ratios	68.75
Right edge density	86.1
Edge depth	86.3
Eye color distance	65.62

The threshold value plays a significant role in producing good results. For example, the threshold of range [30, 60] and [0, 30] produces the accuracy 84.37% and 81.25%

respectively. The interesting point about the edge density feature was that if the edge information in the range [0, 60] is used, then it produces better results (87.5%) comparing to the using to separate feature of range [0, 30] and [30, 60] (71.87%). Therefore, it is very crucial to test different subsets and variations for features.

5.3.Lipstick detection subsystem

Lipstick detection in face is a very challenging problem because of the similarity between the face skin color and lip/lipstick color. The more intense the color is, the easier to identify the lipstick. In this section, the techniques to extract features used for identifying lipstick will be discussed. In the last subsection the result obtained by using the classifier and the features will be presented.

5.3.1. Feature Selection

Because of the different characteristics and shapes of the lips, all the features used for eye are not useful for lips.

5.3.1.1.Edge density and edge depth

Edge density and edge depth are good features used in lipstick recognition, since lipstick and lip-liner add edges around the lip. The sharpened edges are good sign of lipstick. Although most lipsticks add intensity to the lip color, lipsticks with brighter colors exist as well which because of the shiny look they would add small edges to the lip.

(a) (b) (c) (d)

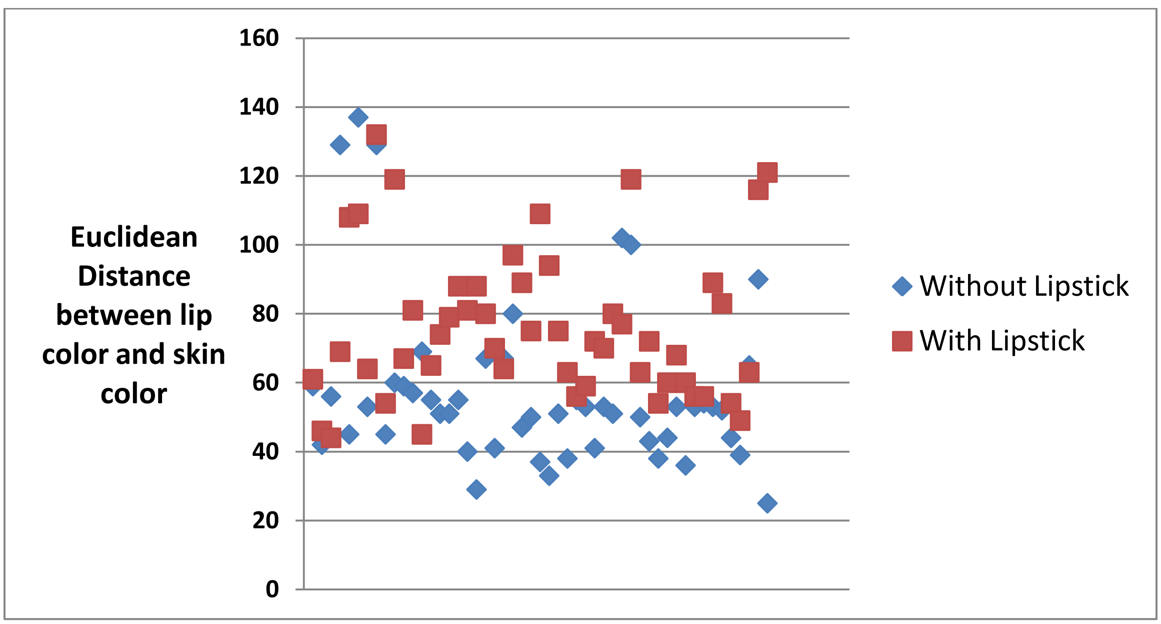
**Figure 5-17 Edge density on lips:
a) photo with no makeup; b) applying edge detector on image (a);
c) photo (a) with makeup and d) applying edge detector on image (c)**

Figure 5-17 shows the effect of Sobel edge detector. It displays that the pattern of edges are different when having lipstick. To retrieve all information about the edges, three threshold ranges was used: [0,30], [30,60] and [60,90].

5.3.1.2. Lip Color Distance

The average Euclidean distance between the lip image and the sample skin is another useful feature in lipstick recognition. Table 5-6 displays the dispersion of these values for the database images of the lips. The chart reveals that most of the lip images had overall distance more than those without lipstick. Therefore combining this feature with other features could be a very good indicator for the lipstick detection application.

Table 5-6 Euclidean Distance between lip color and skin color



5.3.2. Classification

For lipstick recognition in this research, the SVM (Support Vector Machine) classifier is used. The proportion of database division for train and test was 70% for the training and 30% for the testing. The features used in this classification are:

1. Lip edge density with threshold [30,60]

2. Lip edge depth with threshold [30,60]
3. Lip edge density with threshold [60,90]
4. Lip edge depth with threshold [60,90]
5. Lip color distance

5.3.3. Results

The result of SVM classifier with gamma = 0.5 for features described in the previous section is shown in Table 5-7:

Table 5-7 Results of Lip-stick detection with SVM classifier

	No. in testing	Correct Estimate	Wrong estimate
With makeup	15	15 (100%)	0 (0%)
Without makeup	15	13 (86%)	2(13%)

This result is for a classifier with 101 frontal face images, which had 71 images for training and 30 images for testing. The images are spread randomly for training and testing. Half of the testing images were with makeup and the other half without makeup.

The recognition rate for lip-stick was 93.33%. It recognized 28 out 30 images. Figure 5-18 shows the two images that their makeup amount was not detected correctly. Their average color distances (44 and 50) were in right criteria but the edge information was not. One probable reason might be the intense light on the face has distorted the calculations.

Figure 5-18 Two sample images with no lipstick that were not detected correctly

The following table (Table 5-8) shows the result of eliminating features from the classifier. It can be concluded that edge density with threshold [60, 90], Eye color distance and edge density with threshold [30, 60] in order, are the most important features.

Table 5-8 Result of eliminating features in lip-stick detection

Eliminated Feature	Result
Edge density with threshold [30,60]	76.66
Edge depth with threshold [30,60]	83.33
Edge density with threshold [60,90]	90.00
Edge depth with threshold [60,90]	93.33
Eye color distance	83.33

The edge density with threshold [0, 30] was not helpful, and it reduces the accuracy to 83.33%. The edge depth (see section 4.5.2) was beneficial for eye-shadow detection but not for lip-stick recognition. By using this feature and edge density (see section 4.5.1) feature the accuracy is 86.66% which therefore reduce the result to some extent. This means that the edges with low depth are not useful for lipstick recognition.

5.4.Face-foundation Detection Subsystem

Face-foundation is the type of cosmetics used to conceal pimples or wrinkles. Therefore it can be applied partially or completely on the face. In this research for all the images with makeup, liquid-foundation is used on all the faces. However to cover the skin defects more foundation is applied.

5.4.1. Classification

The SVM classifier is also used as a classifier for face-foundation recognition in this research. The proportion of database division for training and testing was 60% and 40% in order. The features used in this classification are:

- Skin edge density with threshold [30,60]
- Skin edge depth with threshold [30,60]
- Skin edge density with threshold [60,90]
- Skin edge depth with threshold [60,90]
- Gabor filter

The next step in this study is to use wavelets as another feature and verify it helps to improve the result. The advantage of using the wavelets is that first by down sampling it reduces the size of the image which increases the speed of the process, second the low coefficients reveal the very fine details of the face skin which might help to get more information about the makeup.

5.4.2. Results

The result of SVM classifier with gamma = 0.5 for features described in previous section is shown in Table 5-9:

Table 5-9 Results of face foundation detection with SVM classifier

	No. in testing	Correct Estimate	Wrong Estimate
With makeup	20	15 (75%)	5 (25%)
Without makeup	20	7 (35%)	13(65%)

The recognition rate for face foundation was 52.55%. It recognized 22 out of 40 images correctly. This result reveals that the recognition rate for faces without face foundation was not satisfactory. The minor changes that are caused by face foundation are not very obvious. The foundation applied on most of the faces in the database was a thin layer only to cover the defects of the skin. For images with more foundation it is easier to some extent.

Figure 5-15, which are two sample fashion photos, the skin is completely retouched and the edges are totally smoothened. This is a method that photographers usually accomplish via a photo editing software such as Photoshop. For these photos, different type of features should be used.

In this chapter a supervised learning model called SVM (Support Vector Machine) classifier is used and the accuracy obtained is 90.62% for eye-shadow detection, 93.33% for lip-stick and 52.5% for liquid foundation detection respectively. A main highlight of this technique is to specify where makeup has been applied on the face, which can be used to identify the proper makeup style for the individual. This application will be a great improvement in the aesthetic field, through which aestheticians can facilitate their work by identifying the type of makeup appropriate for each person and giving the proper suggestions to the person involved by reducing the number of trials.

Chapter 6

6. Conclusions and Future Work

In this final chapter, the summary of contributions of this research as well as future work will be discussed. The need for having an algorithm to analyse beauty standards was the motivation to conduct this research. Beauty has been a great concern in mankind with a long history as well as the digital world. Detecting makeup on human faces and quantifying it is the main purpose of this research. After detecting makeup it would be possible to analyze it from the aesthetic point of view. Since the face characteristics vary from person to person, the appropriate type of makeup could be applied.

Furthermore, aside from the aesthetics point of view, the makeup can totally change the appearance of people. Criminals use different cosmetics and hair colors to be able to change their look dramatically. Security systems that interact with humans and retrieve information based on the digital photo taken by people are vulnerable to face changes. Detecting makeup and then undoing the changes caused by makeup eliminate this deformation from face and facilitate the extraction of required information such as gender, age or identity. This application initially by detecting makeup on face and afterward by specifying their locations can be helpful for many security systems.

Another application of this technique is to report the state of individuals' appearance. In some societies or gathering certain cosmetics or customs are forbidden. For example in Islamic countries it is mostly forbidden for women to wear makeup. A computer system that can process the facial appearance of women and then report it, is a good replacement for the person responsible of doing this job.

A proper database was the main contribution of this research, which required a significant amount of time and effort to gather people and apply makeup. Subsequently, the helpful features in detecting makeup were studied. Color characteristics are useful features in makeup detection, therefore color images are used in this study although many other features are extracted from the grayscale images. In chapter 3 the features and the proposed methodology were described and discussed entirely, and in chapter 4 the results of the classifier have been presented and discussed.

6.1.Database

The novel facial makeup database was collected for this study since none of the published facial databases contain the information of makeup. This database consists of almost 1290 frontal pictures from 21 individuals before and after makeup. Along with the images, some meta data such as ethnicity, country of origin, smoking habits, drinking habits, age, and job is provided. This information is helpful for other facial analysis topics as well. Variation of lighting conditions is another advantage of this database since any changs in lighting will cause difficulty in estimating the existence of makeup. Since the research was done within the university most of the participants were Concordian students, however with different nationalities.

From the pictures, 102 pictures, most suited for the study, were selected. Those which were chosen had indoor light with a single light source. Two series of photos were taken one before and one after makeup. For both series the lighting and its direction varied.

6.2.Methodology

The first step to analyze the facial makeup digital photos is pre-processing. All the images are cropped and resized to the dimension 380x480 and then the histogram equalization is applied to enhance the color qualities.

Since makeup can be applied partially rather than to the whole face, the facial features such as the eyes and the lips were analyzed separately. The techniques and features are different for three face features: eyes, lips and skin. For the eye-shadow detection distinguishing the eye-shadow color from the skin color was important. Otherwise differentiating the dark shadow color with the skin having shadow on it would be complicated. To solve this problem, a rectangular sample is taken from the face (Figure 4-13), starting from bottom of the eyes and ending above the lips. The nostril helps to add the skin color with shadow to the range of possible skin colors for this specific person. With this technique the skin color and shadow color can be distinguished to some extent. However the average distance of eye-area colors with the sample skin's was another good feature used. Other features such as the ratio of edge density and edge depth were also used for the eye-shadow detection.

Although challenging, the recognition of the lipstick was similar to eye-shadow detection. The problem here was to differentiate the hue of the lips and the skin. Color distance is a very effective feature in this process however other features such as edge density and edge depth improve the recognition rate.

Liquid foundation detection on the skin is not straightforward because of its similarity to plain skin. Gabor filter, because of its characteristics that can be applied to different orientations and scales, gives a lot of information about the texture. Along with Gabor filter, the edge data is also used for the foundation detection.

6.3.Summary of Results

The features obtained through each subsystem were finally given to a classifier in order to categorize them. In this study 102 images were used in the SVM classifier. The proportion of database division for the training and testing was 70% and 30% respectively. For the other two subsystems: lipstick and face foundation recognition, the proportion was 60% over 40%. The discrepancy stems from the need for more training images in different settings.

The features used for eye-shadow detection are: invalid colors ratios, edge density, edge depth and color distance. These features are extracted from the eye area upto the bottom of eyebrow. The extracted features are applied on the SVM classifier which produced 84.37% accuracy, meaning 27 out of 32 images were recognized correctly. Among the eye pictures, those with black or brown eye-shadow were more difficult to identify because of the similarity of this color to the skin color with no light (shadow). But, eye-shadow with different colors like blue or pink were much easier to estimate. Another difficulty is with closed eye which distorts the color and texture.

The lipstick recognition subsystem does not need much pre-processing in contrast to the eye-shadow detection. However, selecting the best features is quite challenging for this phase, since the pure color (hue component of HSV color space) of lips is so close to the individual's skin color. Therefore recognizing the lipstick based on its color was impossible. After many experiments and examining different texture features the edge information was found to be the most suitable characteristics. Different threshold ratios ([30, 60] and [60, 90]) and the color distance was used as well. The result produced from the SVM classifier was 93.33%. The reason for wrong estimation of some faces were mostly because of the intense light on the face has distorted the calculations as well as the edges.

The final phase of this project was to detect the face foundation on the skin. Since the goal of using foundation is to cover the skin defects, the color will not be a good feature for this purpose. However, features that are related to texture of the skin are more helpful.

The selected features were: Garbor filter and different edge ratios with threshold ([30,60] and [60,90]). The result for this part was 52.55%. The recognition rate for face foundation was not promising. Normally people use face foundation to have a very smooth skin which looks natural as well. However over using this cosmetic is not very common among women. Therefore usually there is not an obvious difference after applying face foundation.

In conclusion, good results were obtained from this algorithm. However, with more images in the database it can be improved. A main highlight of this technique is to specify where the makeup has been applied on the face, which can be used to identify the proper makeup style for the individual. Moreover, the technique described earlier is color invariant, so for different skin colors this technique still produces good results. In fact the idea of these techniques is based on many texture and skin analysis techniques. The result obtained from this thesis is useful for other areas of research like human skin analysis and texture detection and analysis as well. This algorithm is not robust against the pose and gesture changes, it challenges in illumination change as well.

6.4.Future work

Detecting makeup on face is a preliminary research done about makeup on digital images. Since both face image analysis and makeup techniques are vast fields, this research could be improved. Some suggestions about future work are presented below:

1. Because of the limitations of the budget and time for a Master's thesis, the process of collecting participants eager to participate in this new makeup facial database was limited to 5 months. To produce a better database, more participants are needed. Moreover, many new types of cosmetics can be applied on women's face.
2. This research can estimate if the person has makeup or not, which is studied only on the images of the new database and not the images from other sources such as web. Nowadays most images of face are retouched by software such as the

Photoshop. Sometimes it is helpful to find out which photos are not retouched and which are.

3. After studying the image, we can decide whether this makeup from an aesthetic view point is suitable for this face or not. Makeup artists have some rules that help them to produce better makeup for the face. They look at the size and distance of the eyes, size of lips and face shape (discussed in section 3.2.3).
4. Variation in the face pose and the illumination causes difficulty to recognize makeup. Being able to analyze the makeup under different conditions is a big challenge, which was beyond the scope of this research.
5. To study the human skin, techniques with a higher accuracy are needed since the changes on the skin are usually very subtle and not obvious.
6. To train the system, different combinations of blur, motion and noise can be applied to the images and then repeat the process. The database used for this research contains images with high quality and standard sizes. Testing the algorithm with arbitrary pictures or webcam photos, which are captured with low accuracy and resolution, can be a major challenge [60].

References

[1] A. Bottino and A. Laurentini, "The Analysis of Facial Beauty: An Emerging Area of Research in Pattern Analysis," *Lecture Notes in Computer Science,* vol. 6111, pp. 425-435, 2010.

[2] M. Brand and P. Pletscher, "A conditional random field for automatic photo editing.," *IEEE Conference on Computer Vision and Pattern Recognition,* pp. 1-7, 2008.

[3] W.-S. Tong, C.-K. Tang, M. S. Brown and Y.-Q. Xu, "Example-based cosmetic transfer," *Conference on Computer Graphics and Applications ,* pp. 211 - 218 , 2007.

[4] M. Osadchy, B. Pinkas, A. Jarrous and B. Moskovich, "SCiFI - A System for Secure Face Identification," *IEEE Symposium on Security and Privacy (SP),* pp. 239 - 254, 2010.

[5] September 2012. [Online]. Available: http://www.scholarpedia.org/article/Facial_Age_Estimation.

[6] K. Luu, "Computer Approach for Face Aging Problems," Montreal, 2009.

[7] September 2012. [Online]. Available: http://www.fgnet.rsunit.com/.

[8] H. T. Greene and S. L. Gabbidon, "Overview of Race, Ethnicity, and Crime," in *Race and Crime*, SAGE Publications Inc, 2012.

[9] C. C. Chibelushi and F. Bourel. [Online]. Available: http://homepages.inf.ed.ac.uk/rbf/CVonline/LOCAL_COPIES/CHIBELUSHI1/CCC_FB_FacExprRecCVonline.pdf.

[10] F. Naini, Facial Aesthetics: Concepts and Clinical Diagnosis, 1 ed., John Wiley & Sons, 2011.

[11] N. Etcoff, "Beauty and the Beholder," *Nature,* vol. 368, pp. 186-187, 1994.

[12] L. Cosmides, J. Tooby and J. Barkow, The Adapted Mind: Evolutionary Psychology and the Generation of Culture, Oxford University Press, 1992.

[13] D. Zhang, Q. Zhao and F. Chen, "Quantitative analysis of human facial beauty using geometric features," *Pattern Recognition,* vol. 44, pp. 940-950, 2011.

[14] J. Langlois and L. Roggman, "Attractive Faces Are Only Average," *Psychological Science,* vol. 1, pp. 115-121, 1990.

[15] T.-D. L. a. P. M. H. Bernstein, "Cross- vs. within-racial judgments of attractiveness," *Attention, Perception, & Psychophysics,* vol. 32, no. 10.3758/BF03204202 , pp. 495-503, 1982.

[16] C. Samuels and R. Ewy, "Aesthetic perception of faces during infancy," *Devolpmental Psychology,* vol. 3, p. 221–228, September 1985.

[17] F. Naini and D. Gill, "Facial Aesthetics: 1. Concepts and Canons," *Dental Update,* vol. 35, pp. 102-107, 2008.

[18] Z. Frank, Leonardo Da Vinci (1452-1519), Germany: Taschen, 2000.

[19] September 2012. [Online]. Available: http://en.wikipedia.org/wiki/Vitruvian_Man.

[20] September 2012. [Online]. Available: http://www.goldennumber.net/beauty/.

[21] J. Cross and J. Cross, "Age, Sex, Race, and the Perception of Facial Beauty," *Developmental Psychology,* vol. 5, pp. 433-439, 1971.

[22] J. Halberstadt and G. Rhodes, "The attractiveness of non-face averages: Implications for an evolutionary explanation of the attractiveness of average faces," *Psychological Science,* vol. 11, pp. 285-289, 2000.

[23] T. Alley and M. Cunningham, "Averaged faces are attractive, but very attractive faces are not average," *Psychological Science,* vol. 2, pp. 123-125, 1991.

[24] K. Grammer and R. Thornhill, "Human (Homo sapiens) facial attractiveness and sexual selection: the role of symmetry and averageness," *Journal of Comparative Psychology,* vol. 108, pp. 233-242, 1994.

[25] Y. Eisenthal, G. Dror and E. Ruppin, "Facial Attractiveness:Beauty and the Machine," *Neural Computation,* vol. 18, pp. 119-142, 2006.

[26] P. Aarabi, D. Hughes, K. Mohajer and M. Emami, "The automatic measurement of facial beauty," *IEEE International Conference on Systems, Man, and Cybernetics,* vol. 4, pp. 2644 - 2647, 2001.

[27] D. Guo and T. Sim, "Digital face makeup by example," *IEEE Conference on Computer Vision and Pattern Recognition,* pp. 73-79, 2009.

[28] J. Manning, L. Morris and N. & Caswell, "Endurance running and digit ratio (2D:4D): implication for fetal testosterone effects on running speed and vascular health," *American Journal of Human Biology,* vol. 19, pp. 416-421, 2007.

[29] N. Etcoff, Survival of the Prettiest: The Science of Beauty, New York: Anchor, 2000.

[30] D. I. Perrett, K. A. May and S. Yoshikawa, "Facial shape and judgements of

female attractiveness," *Nature,* vol. 368, pp. 239-242, 1994.

[31] September 2012. [Online]. Available: http://barefacedtruth.com/2012/01/18/a-brief-history-of-skin-care-cosmetics-part-1-ancient-times/.

[32] "History of Cosmetics," September 2012. [Online]. Available: http://en.wikipedia.org/wiki/History_of_cosmetics.

[33] R. Moris, Makeup: The Ultimate Guide, Allen & Unwin, 2008.

[34] September 2012. [Online]. Available: http://www.wisegeekedu.com/what-is-a-fashion-makeup-artist.htm.

[35] September 2012. [Online]. Available: http://www.suite101.com/content/permanent-makeup-pros-and-cons-a145836.

[36] N. Ojima, K. Yoshida, O. Osanai and S. Akasaki, "Image synthesis of cosmetic applied skin based on optical properties of foundation layers," *In Proceedings of International Congress of Imaging Science,* p. 467–468, 1999.

[37] D. Guo and T. Sim, "Digital Face Makeup by Example," *IEEE Conference on Computer Vision and Pattern Recognition,* pp. 73 - 79, 2009.

[38] R. .. Gross, I. S. Li and A. Jain, "Face Databases," *Handbook of Face Recognition. Springer Verlag,* pp. 301-327, 2005.

[39] [Online]. Available: http://www.ourvanity.com/beauty/makeup/make-up-based-on-eye-shape/.

[40] September 2012. [Online]. Available: http://www.ourvanity.com/beauty/makeup/make-up-based-on-eye-shape/.

[41] M. Escarra and M. Robinson, "Face Recognition Background," September 2012.

[Online]. Available: http://cnx.org/content/m12535/latest/.

[42] M. Kirby and L. Sirovich, "Low-dimensional procedure for the characterization of human faces," *Optical Society of America,* vol. 4, pp. 519-524, 1987.

[43] M. Turk and A. Pentland, "Face Recognition using Eigenfaces," *IEEE Conference on Computer Vision and Pattern Recognition,* pp. 586-591, 1991.

[44] M. Turk and A. Pentland, "Eigenfaces for Recognition," *Journal of Cognitive Neuroscience,* vol. 3, pp. 71-86, 1991.

[45] M. Hamouz, "Feature-Based Affine-Invariant Localization of Faces," *IEEE Transactions on Pattern Analysis and Machine Intelligence,* vol. 27, no. 9, pp. 1490 - 1495 , 2005.

[46] P. Viola and M. Jones, "Robust real-time object detection," *International journal of computer vision,* vol. 57, pp. 137-154, 2004.

[47] D. Zhou, D. Etrovska-Delacretaz and B. Dorizzi, "Automatic Landmark Location with a Combined Active Shape," *IEEE 3rd International Conference on Biometrics: Theory, Applications, and Systems,* pp. 1-7, 2009.

[48] T. Coots, "Model-Based Methods in Analysis of Biomedical Images," in *Image Processing and Analysis*, Oxford University Press, 2000, pp. 223-248.

[49] S. Milborrow and F. Nicolls, "Locating Facial Features with an Extended Active Shape Model," *SpringerLink,* vol. 5305, pp. 504-513, 2008.

[50] M. B. Stegmann and D. Gomez, "A Brief Introduction to Statistical Shape Analysis," Lyngby, 2002.

[51] S. Milborrow, "Locating Facial Features with Active Shape Models," Faculty of Engineering, University of Cape Tow, M.Sc. Thesis, 2007.

[52] September 2012. [Online]. Available: http://igee.umbb.dz/document/CHERIFI_RADJI_NAIT-ALI_Pub.pdf.

[53] R. C. Gonzalez and R. E. Woods, Digital Image Processing, Prentice Hall, 2008.

[54] A. Ford and A. Roberts, "Colour Space Conversions," September 2012. [Online]. Available: www.poynton.com/PDFs/coloureq.pdf.

[55] Intel, "Image Color Conversion," September 2012. [Online]. Available: http://software.intel.com/sites/products/documentation/hpc/ipp/ippi/ippi_ch6/ch6_Intro.html.

[56] D. Cardani, "Adventures in HSV Space," September 2012. [Online]. Available: visl.technion.ac.il/labs/anat/hsvspace.pdf.

[57] A. T. Tuan, M. Song and K. Young, "Shadow Detection and Effect Evaluation on a Face Image Using Automatic Threshold Selection," *The Journal of Korea Institute of Information Technology,* vol. 9, no. 11, pp. 98-106, 2011.

[58] W. Horng, C. Lee and C. Chen, "Classification of Age Groups Based on Facial Features," *Tamkang Journal of Science and Engineering,* vol. 4, no. 3, pp. 183-192, 2001.

[59] T. Sergios and K. Konstantinos, Pattern Recognition, Canada: Elsevier, Academic Press, 2009.

[60] V. I. Uzunova, "An Eyelids and Eye Corners Detection and Tracking Method for Rapid Iris Tracking," Otto-von-Guericke University,Department of Computer Science(Image Processing Group), M.Sc. Thesis, Magdeburg, 2005.

[61] D. Cherifi, N. Radji and A. Nait-Ali, "Effect of Noise, Blur and Motion on Global Appearance Face Recognition based Methods performance," *International Journal of Computer Applications,* vol. 16, no. 6, pp. 4-13, February 2011.