Analysis of Facial Emotional Characteristics: Impact of Culture and Gender

by

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Author's Declaration

I hereby declare that I am the sole author of this thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.

I understand that my thesis may be made electronically available to the public.

Abstract

Emotional expressions are considered universal for a long time. However, some evidence indicates that there are gender and cultural specific variations in emotional expressions, which leads to inaccurate recognition result in the emotion recognition system. Therefore, this thesis aims to identify the particular cultural and gender variation in basic facial expressions (disgust, fear, happiness, surprise, and sad) in terms of action units that are defined by the facial action coding system (FACS). A logit regression is conducted with each emotions' action unit as independent variables and race (Caucasian and Asian) as the dependent variable. The result reveals that each emotion expression's specific action units in Caucasian and East Asian are different. This thesis also constructs four average faces regarding culture and gender to evaluate the gender variability of action unit intensity in the same cultural group. The finding indicates less distinction in Caucasian facial behaviors compared with Asian, and women are generally more expressive than men.

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Last, I would like to thank my family for the love and support throughout my graduate study. Without their encouragement, I can't be who I am now.

Dedication

This is dedicated to my family.

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List of Abbreviations

AU Action Unit 3

BET Basic Emotion Theory 2

BP4D Binghamton-Pittsburgh 3D Dynamic Spontaneous Facial Expression Database 20

CK Cohn-Kanade ix

CK+ Extended Cohn-Kanade ix

CVP Cultural Variant Patterns 14

FACS Facial Action Coding System 2

HOG Histograms of Oriented Gradients 20

ICP International Core Patterns 13

JACFEE Japanese and Caucasian Facial Expressions of Emotion 14

SEMAINE Sustained Emotionally coloured Machinehuman Interaction using Nonverbal Expression 20

TFEID Taiwanese Facial Expression Image Database ix

Chapter 1

Introduction

1.1 Background

As societal information and a nonverbal communication method, facial expression was regarded as a universal language in social animals and humans[6]. The application of facial expression recognition is widely in many areas. In autonomous driving, the camera in a driver emotion recognition system can monitor the driver's facial behaviors. If an extreme emotion is detected, the system will regulate the driver's emotions by playing soothing music to avoid accidents since drivers with excessive activation levels of emotions are 2.3 times more likely to be involved in a traffic crash than emotionally stable drivers[7][8].

However, some facial recognition models' perform better in Caucasian facial expressions than the Asian. The difference in performance may be caused by uneven race in training data. Models are majorly trained on Caucasian facial images due to the East Asian facial expression dataset is limited.

To address this problem, this thesis identifies the cultural and gender variation in facial expression between Caucasian and East Asian. Most studies that examine cultural accent only suggest its existence without identifying the specific variation. Jack et. al. indicate that the mental reconstruction of East Asian and Caucasian facial expression are different[3], but they don't conclude the cultural preference in facial expression. Cordaro et al. suggest some cultural bias, but the proposed pattern are not consistent with most commonly accepted emotion theories[5]. Besides, limit studies are conducted on gender variation. Given that, this thesis aims to recognize the specific cultural and gender preference in terms of facial muscle movement and intensity, and explain the observation. The finding of this thesis can assist the facial recognition system in interpreting the driver's emotional situation.

In this thesis, only six basic emotions (happy, anger, sad, disgust, fear, and surprise) are examined since psychologists believe that six basic emotions can express the full range of complex facial behaviors. Besides, a commonly accepted system, Facial Action Unit System (FACS), is employed to decode the basic emotions in terms of facial muscle movement[9]. In this section, the thesis introduces the development of basic emotion theory (BET), evaluation of FACS, and clarifies the relation of culture and gender to facial expression.

1.1.1 Basic Emotion Theory

Ortony and Turner believe that researchers are unable to find basics emotions due to the lack of satisfactory basic criteria[10]. Their claims are derived from the viewpoint that emotions are generated based on multiple types of cognition. The so-called basic emotions are not "psychologically primitive" or "biologically primitive". Thus, they conclude the entire spectrum of emotions can't be represented by basic emotions [11][10].

However, many theorists of emotion influenced by contemporary ethology declare that emotions are reconstructed by natural selection. Emotions are also the reactions to the enormous possibilities in the environment[12][13]. Base on that, the belief that emotions are central to evolution brings a different meaning to the definition of basic emotion. This belief leads to a series of universal emotion principles that can be subjected to a framework to describe the broad range of emotional interactions[11].

Thus, in contrast with Ortony and Turner's opinions, Izard proposes that basic emotions should have intrinsic neural substrates. The facial pattern of basic emotion has to be distinctive and widely known, and it can represent a unique state of feeling[11]. Along with these empirical studies, BET approach is inspired. The core hypothesis of BET is foundational to much empirical progress in understanding the mechanism of emotion-related physiology and psychology[14]. The earliest study of BET can be traced back to the study of New Guinean's experiment, which is detailed discussed in the section 2.3[14][15]. Ekman and Friesen document a set of universally recognised emotions that are widely accepted as basic emotions, including happy, sad, anger, surprise, fear, and disgust[15], and the example of basic emotional expressions are shown in fig. 1.1. Lots of scientists are inspired by their work[14], resulting in many replicated studies. These studies conclude that observers can accurately classify the six basic emotions with some degree of confidence from static facial expressions images[2].

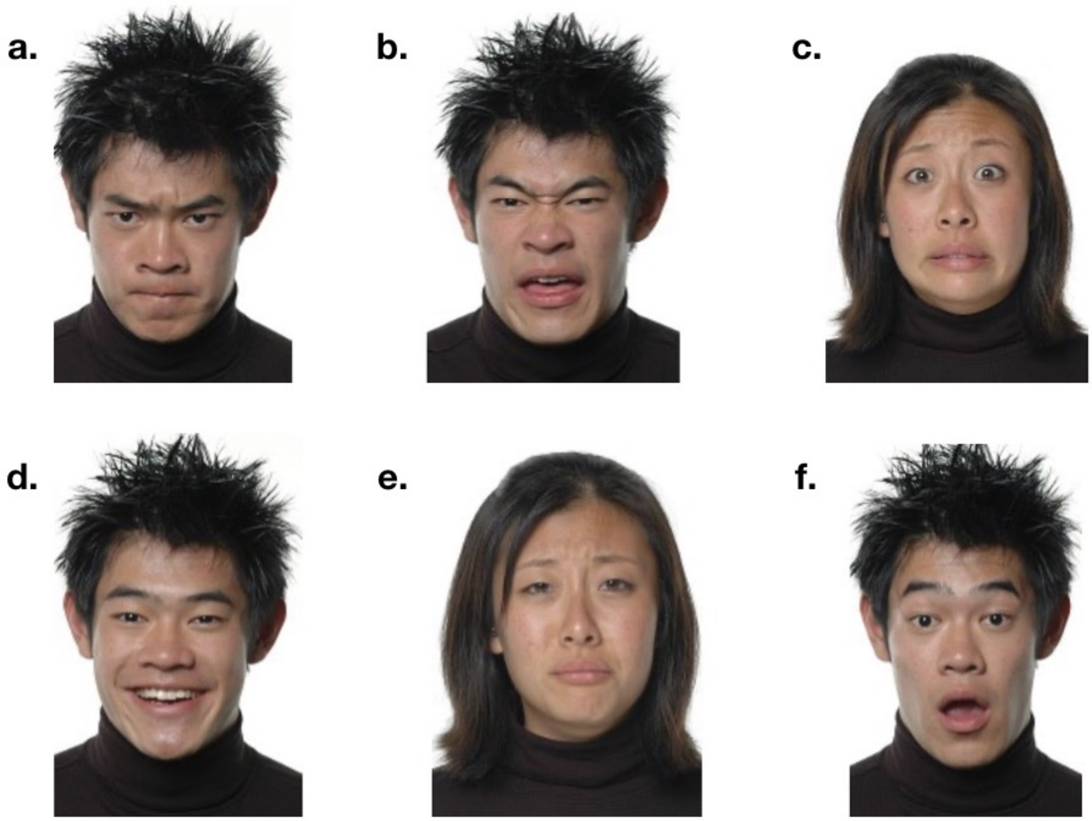

Figure 1.1: Example of six basic facial expressions, including (a)anger, (b)disgust, (c)fear, (d)happy, (e)sad, and (f)surprise.[1]

1.1.2 Facial Action Unit System

FACS, the most commonly used systemic facial expressions framework, describes facial activity with a view of anatomy. It is a human-observer-based system that correlates facial muscle movement with basic emotional expressions(happy, sad, disgust, fear, surprise, and anger[16][17][9].

With FACS, facial expressions are decomposed into 44 action units (AUs). Each AU represent a specific facial muscle movement. Among the 44 AUs, 30 of them are defined with support of anatomic basis (e.g., lift the brow), while the left 14 AUs illustrate some other behavioral movements(e.g., jaw thrust)[18]. Specific combinations of AUs, known as facial configurations, interpret facial expressions. Many studies of facial expression employ this framework to analyze facial behavior and various facial configuration theories are proposed[19]. Some main involved AUs in facial expressions is illustrated in fig. A.1[1].

FACS has an overall good to excellent performance on reliability tests for facial expressions, and most of the AUs (90%) are vital in emotional expressions. Most AUs can be clearly differentiated. However, AU7 (lid tightener) and AU23 (lip tightener) show fair reliability. AU 7 (lid tightener) are often mistaken for AU6 (cheek raiser) since they are governed by the same facial muscle. AU23 (lip tightener) are often mistaken for AU24 due to the same reason[20]. Despite that commonly mistaken AUs, FACS is a standard measure for facial expressions, and it has wide applications in many fields[21].

1.1.3 Gender Influence

Psychologists conduct researches on gender influence and conclude that many inconsistencies exist in the result associated with methodological problems[19][22]. For example, from reported emotional responding patterns in expressive aspects, females generally reveal unpleasant emotions (e.g. sad and fear) more frequently, while males reveal hostile emotions (e.g. anger), but latter studies demonstrates this finding is not reliable[22].

Two explanations are proposed to interpret the gender variation. Some researchers state that gender difference in emotion results from gender-biased socialization and stereotyping in cultural and social contents[23][24]. Fischer and her colleagues further explain this theory with an example. In western societies, women's possibility to take nursing roles and provide emotional care is higher than men's. In contrast, men are more likely to take the roles that provide material resources (e.g., a paid job in a company) instead of emotional resources. This illustration indicates that women prefer fewer power roles than men in some cultures. Distinct facial expressions are resultant of various social roles[25]. Another alternative explanation concludes that the gender difference in emotion is caused by biological differences[25]. For instance, hormonal effects explain the more frequent negative facial expressions, like crying, of women[26][27]. Besides, Wood and Eagly emphasize the effect of social roles in analyzing gender differences in social behavior[28]. Their studies support the hypothesis that gender differences result from the interaction between physical aspects and socialization[25].

With the adoption of the two explanations above, researchers conclude that the difference in emotional expression mainly stems from cross-cultural variation in gender roles[25].

1.1.4 Cultural Influence

Some empirical studies show that cultural learning can modify the inborn expressive pattern. They indicate that facial expression is shaped by cultural values and cultural learning[5][29]. Ekman and Friesen interpret that the display rule is one of the significant aspects that induce cross-cultural variation [30][31]. The display rule address a scenario that people should not show unpleasant facial expression in working places in some specific cultures[32]. Moreover, display rule differs among ethnic groups, which further support cultural influence on facial expressions[33].

Despite display rule, decoding rule is another approach that interprets cross-cultural variability . For instance, members within some cultural groups tend to avoid spread negative emotions to other members to raise social harmony[32].

Some other researchers describe the cross-cultural difference in facial expressions by linking recognised differences with dimensions of cultural variability, including power distance, individualism, masculinity, uncertainty avoidance, and status differentiation.

[31] also proposes that the effect of language is one of the confounding factors in cross-cultural facial expression studies. Matsumoto and Ekman conduct studies on the labelling language in Japanese and American and do not find the difference. However, another study showed that bilingual Indian students label emotion judgments more accurately with English labels than Hindi labels.

1.2 Thesis Objectives

The goal of this thesis is exploring facial expressions variability in terms of gender and culture. For the cultural variation, Caucasian and Asian facial behaviors are selected due to the huge diversity of western and oriental civilizations. The thesis focus on specific facial configuration differences between two cultural group and facial expression intensity variation of male and female. The main contributions could be summarised as:

- Identify facial configuration variability in Caucasian and Asian
- Interpret the cultural variation in facial behaviors based on relative psychology research.
- Compare facial expression intensity in male and female with same cultural background

- Interpret gender variation in facial expression in the view of psychology and sociology.

1.3 Outline

Chapter 2 first overviews the perception of emotions from the universal hypothesis to the belief that emotions are not universal, then discusses the diverse factors that reshape facial expressions in the literatures.

Chapter 3 states the methodology of this thesis and introduces the datasets (Caucasian and East Asian) used in exploring the culture and gender variation. In the cultural impact section, a logit regression is used to examine the significant facial configurations in two racial groups. In the gender impact section, some ethnic average facial expressions with respect to gender are constructed. Then, the AU intensity can be extracted from the generated faces. Finally, the summary statics about the AU intensity between two genders are computed to explore the gender variability further.

Chapter 4 discusses the regression results in each basic emotion expression and evaluates the observations with other studies. This chapter also indicates some limits in model construction and the process of AU detection.

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Chapter 5 discuss the gender variability in Caucasian and East Asian basic facial expressions. It also describes the limit in this gender study according to the datasets and data processing method.

Chapter 6 summaries the thesis, highlight some major observations and discuss some further work that can be done.

Chapter 2

Related Work

2.1 Introduction

The previous section demonstrates how humans encode and decode emotional expressions and reveal the correlation between facial behaviors and socialization. In this section, the researchers' perceptions of emotion are reviewed. Emotion is perceived as a universal language in the early study[6]. Later, some studies dispute the universal hypothesis and discourse that many factors, including culture and gender, can reshape facial expression[34][35]. Thus, some vital studies and the corresponding experiment setup, major contributions and limits, that demonstrate the psychologists' knowledge of emotion are also discussed. From these studies, two assumptions that this thesis sets the foot are derived:

- Facial configuration of emotion is reshaped by culture
- The gender differences in facial expression is related to emotion intensity

2.2 Universal Hypothesis

Facial expression is known to be universal for a long time. It is regarded as the shared language, recognizable across diverse races and cultures, as Darwin mentioned in "Expression of the Emotions in Man and Animals" [6]. To test this universal statement, Ekman et al. conduct experiments on an island in the southeast of New Guinea. Until the 1950s, this island was considered isolated by modern society. The chosen participants from islanders in this experiment consist of adults and children, males and females. Besides, these participants had never spoken English or Pidgin. Participants are told a story about a single emotion and then asked to choose the Western facial expression's photograph that best matches the emotion of the story[15].

In addition, researchers videotape New Guinean's posed facial expressions. Some college students from the United States are asked to judge these New Guinean facial expressions from videos, and the judgements show that these students can correctly recognise these facial expressions[15].

The outcome clearly shows that particular facial expressions represent the pan-cultural aspect. Even though the selected New Guineans have almost no cognition of Western facial behaviors, they still can recognise them. Meanwhile, American students can identify New Guinean's facial behvaior, too. Ekman et al. also suggest the potential limit for this experiment. Although the participants are deliberately chosen and never have in-depth interaction with Caucasians or exposure to western countries, they may still have some degree of communication with Caucasian. Hence, they may have observed Caucasian cultural-specific facial behaviors. However, Ekman and Friesen indicate that women, who are less likely to be exposed to Caucasian and western culture than men, perform as well as men. Hence, it can be inferred that selected New Guineans are not acknowledged about western facial behaviors[36].

However, there is a recognised exception, which is fear. Participants can differentiate fear from sad, anger, disgust, and happiness. However, they mistake it for the surprise, while they can correctly distinguish surprise from fear[15]. New Guineans do not discern fear from surprise, so fear in their society has not been separated from surprise because fearful accidents are often associated with surprising incidents[36]. This study implies that the ability to differentiate and recognise facial responses is affected by cultural environment, which is further discussed in section 2.3.

The work of Ekman et al. supports Darwin's universal theory[6]. However, the experiment results can only suggest that Western observers can differentiate inborn facial expressions posed by individuals in a neolithic culture that has not been influenced by Western culture. The result does not suggest whether facial expressions can be accurately recognized by individuals from distinct, highly advanced cultures.

Thus, in order to investigate facial expression recognition between highly developed and modernized cultures, Ekman et al. conduct another experiment. College students from the Undated States and Japanese are asked to watch films that can regulate emotions. Their facial expressions are videotaped without acknowledgement. Then another participant, the observer, enters the lab and discusses the film with the students. During this time, the facial expressions of the students are recorded again[15].

By analyzing the participants' facial expressions before the discussion session, Ekman and his colleagues observe similar facial expressions. Students' frequency of emotional expressions is strongly correlated. In contrast, the facial response of the participants varies throughout the discussion. Japanese students appear to disguise their negative feelings with smiley faces, whereas American students do not alter their facial behaviors during the discussion[15].

From the observation, similar facial responses to the same stimulus are carried out by people of varying cultural backgrounds. Despite that, Japanese students prefer to mask their negative feelings to be more respectful on a social occasion, while American students do not. This phenomenon about Japanese students' facial expression preference is explained by the display rule[37]. Thus, Ekman and Freisen's work affirm the universal theory and display rule.

Thus, it is assumed that inborn facial expression is universal, but cultural learning modifies the facial response in personality growth.

2.3 Cultural Differences in Facial Expressions

As discussed before, researchers doubt the universal theory and perform cross-cultural comparisons. Matsumoto and his colleagues interpret culture as the systematic information that is transmitted generation by generation. They state culture can sustain social order by constructing standards. In specific circumstances in the group, standards guide thinking, feeling, and anticipated behaviors. Moreover, standards are highly correlated with emotions' control since emotions are derived from human behaviors and motivations[34]. Besides, as mentioned in section 2.2 about the observation of Ekman and Freisen's experiment, Japanese mask the unpleasant emotion in public places due to cultural learning. Thus, the psychologists conclude that culture has a significant impact on the emotional expressions of people[38].

Related works about cultural variation in facial response largely concentrate on emotion recognition data—participants' performance on labelling basic emotions categories are documented and analyzed. Elfenbein and Ambady use meta-analysis to summarize 87 studies, in which over 22,000 participants from more than 20 countries are involved in interpreting facial configurations of emotions and various stimuli. Most participants are sampled from larger or developing nations (e.g., Argentina, Canada, China, Germany, etc.). Most of these studies (around 95%) use posed facial behavior; Only 4 studies ask participants to classify spontaneous emotional expressions[1][2].

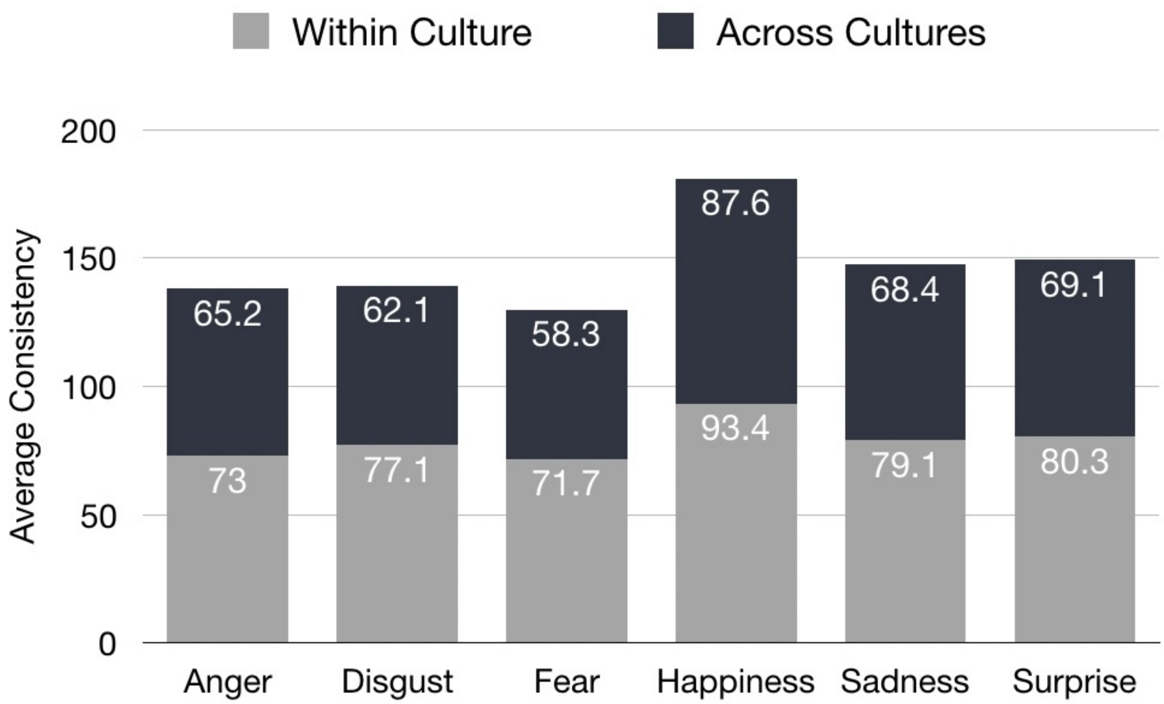

Figure 2.1: Emotion-perception findings[2][1]

The result of meta-analysis in 2.1 presents strong evidence that participants accurately interpret the emotional expressions posed by individuals from their own culture. When participants identify facial configurations posed by people from other cultures, only modest degrees of reliability are observed. This variation in recognition reliability between same- and cross-cultural difference is called in-group advantages[2][1].

However, most emotion-perception experiments do not disclose if the proposed facial structures are interpreted with certain specificity. For example, people often perceive happy emotions with upturned corners of the mouth. The possibility of a grin to be recognized as happy is unclear. Thus, no firm assumptions can be made about the emotional expressions categories of the facial configuration without details about specificity in 2.1[1].

In addition to experiments of "choice-from-array tasks," scientists also reversely correlate facial configuration with emotion categories to find the cultural differences. Jack et al.

employ some cross-cultural participants (West Caucasian and East Asian) that are served as observers. A computer graphics platform randomly generate animations of different combinations of facial movements based on FACS. The participants classify these animations into various emotional categories (only when the animations match with their mental representation) and label the intensity of emotion from 1 to 5 (1 was "very low" and 5 was "very high"). Thus, researchers are able to capture facial expressions' representation models that are correlated with participants' cultural exposure from the classification results. They further explore the reconstructed models by cluster analysis and find evidence in facial expressions' cultural variation[3].

Their study suggests that there is a culturally unique portrayal of the facial expression of East Asian. Thus, facial expressions are not universal. Moreover, they also find some cultural variation in AU intensity expression in Fig. 2.2. East Asian models predominantly express the emotional intensity of happiness, fear, disgust, and anger with facial muscles in eye regions, while West Caucasian models express emotional intensity with other facial muscles[3].

However, the work of Jack et al. only demonstrates the presence of cultural variance in facial expressions and illustrates that West Caucasian and East Asian display emotional intensity differently. The precise cross-cultural variation in facial configuration has not been studied. Hence, cultural specific AU combination is still unclear. Besides, although Jack et al.'s results distinguish cross-cultural facial expressions in the dimension of AU, they have not taken gender into account. Gender also has an influence on facial expressions as a product of gender roles and gender inequality[39].

Table 2.1: Description of Action Unit Correlated with Behavioural Gesture

AU	**Description**
43	Eyelids drooping
53	Head up
54	Head down
55	Head resting on hand
56	Head tilted
64	Eyes down

Moreover, Cordaro and his collaborators further analyze cultural variation in the facial configuration of emotional expression, which extends Jack et al.'s study[3][5]. Cordaro et al. analyze cultural differences in five cultures (China, India, Japan, South Korea, and the United States) by decomposing facial expressions into AUs and identify key AU variations in different cultural-specific facial. Besides the basic emotions, this research also includes

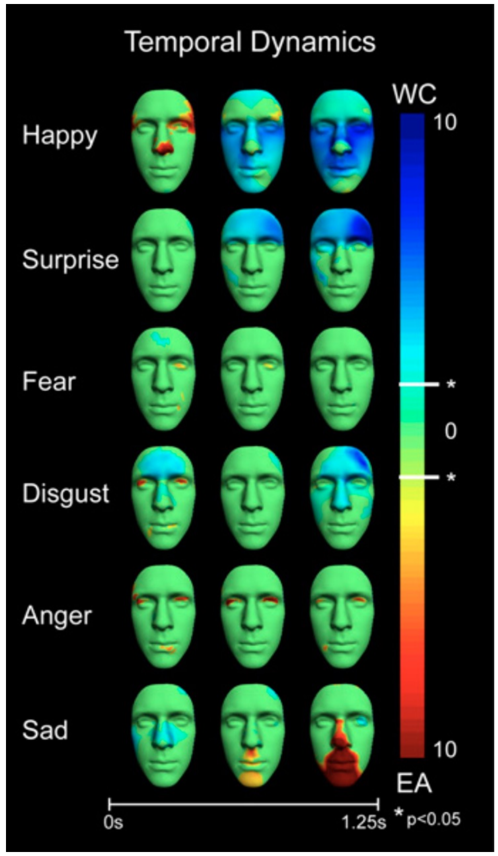

Figure 2.2: Spatiotemporal position of the portrayal of emotional intensity in Western Caucasian and East Asian groups. Color-coded faces in each row show the culture-specific spatiotemporal position of expressive features indicating emotional intensity[3]

some other positive emotions(e.g., amusement, awe, contentment, coyness, desire towards food, desire towards sex, happiness, interest, pride, relief, surprise and triumph) and negative emotions(e.g., anger, boredom, confusion, contempt, disgust, embarrassment, fear, pain, sadness, shame, and sympathy). Many native college students are recruited to present 22 non-verbal emotional expressions. Some one-sentence stories that describe a scenario associated with emotions are translated into the participants' mother tongues. These stories are used as stimuli in the experiment. For example, the story about happiness is, "you have just met your friend and feel very happy that your friend is here." Participants openly share appropriate spontaneous emotional expressions depending on the stories they have told. The expanded FACS, which contains both facial muscle movements and be-

Table 2.2: Cultural Variant Patterns of Six Basic Emotions[5]

Emotion	**CVP**			
	China	**Japan**	**Korea**	**USA**
Anger	17, 27	12, 17, 24, 25, Jaw	25, Jaw, 54	5, 25
Disgust	54	17, 54, Lean Forward	12, 17, 54	19
Fear	4, 12, 16, 20, 25, 52, 54, eyes turn left or right	4, 12F, 16, 20, 54	4, 6, 12	4, 12, 16, 20, 21
Happiness	None	None	None	Head tilts left or right
Sadness	14, 17, 64	6, 7, 25, 64, hand covers face	6, 7, 15, 17, 25, Jaw, 64	15, 17, 64
Surprise	53	12, 53	Head tilts up or down	4

Note: numbers in the table refer to the index of AU.
Besides, AU followed by "F" indicate it only display in females.

havioural gestures (e.g. posture, breathing, head acts, etc.), is used to code the recorded facial expressions.[9][40].

Table 2.3: Reference FACS and International Core Patterns of Six Basic Emotions[5]

Emotion	**Reference FACS**	**ICP**
Anger	4 + 5 + 7 + 23	4, 7
Disgust	9 + 15 + 16	4, 6, 7, 9, 10, 25, Jaw
Fear	1 + 2 + 4 + 5 + 7 + 20 + 26	1, 2, 5, 7, 25, Jaw, Move Back
Happiness	6 + 12	6, 7, 12, 16, 25, 26, Jaw
Sadness	1 + 4 + 5	4, 43, 54
Surprise	1 + 2 + 5 + 26	1, 2, 5, 25, Jaw

Note: numbers in the table refer to the index of AU

By analyzing the documented AU patterns, researchers conclude some ICPs, which are the cross-cultural AU patterns observed, that corresponding to positive and negative facial expressions. Given only six basic emotions are involved in this thesis, table 2.3 only lists six basic emotions (anger, disgust, fear, happiness, sadness, and surprise). The descriptions of each AU can be found in fig. A.1 and table 2.1. ICP is chosen when the specific AU's frequency of presence in facial behavior is higher than the average among all cultures, and a t-test is utilized to cross-examine the chosen threshold. Besides ICP analysis, researchers also conclude some key CVP, which are the AU patterns that only have a higher frequency of presence than average in a specific culture. The CVP of East Asian (China, Japan, Korea) and West Caucasian (USA) is shown in table 2.2.

Cordaro et al.'s study identifies the existence of cultural accents in the facial expressions of five cultures. They verify that there are unique and specific cultural accents in every culture, and cultural differences in emotional patterns are presented. They also suggest that the cultural differences are neither isolated to individual emotions nor various cultures. In contrast, cultural variation is a reliably recorded and systemic behavior in the presentation of emotion[5].

Although this study doesn't consider gender, the observation in cultural variation is still reliable since gender can not influence the facial configuration[41], which is discussed in 2.4. However, as mentioned before, the stimuli used are the one-sentence stories that describe an emotional situation, which is not enough to induce spontaneous emotion. Hence, all facial responses are actually posed expressions. The generalizability of posed expressions is questionable. It is not clear whether the participants have done a decent job of presenting the posed emotions[42].

2.4 Gender Differences in Facial Expressions

Women's greater consistency in determining the emotional meaning of non-verbal signals is well known[43]. In empirical research, Hall and Matsumoto provide in-depth analysis to examine discrepancies between genders' facial expressions. The study is similar to "choice-from-array tasks" described in section 2.3. Participants are all college students of two genders. They are shown each of the facial expressions from JACFEE one by one for 10 seconds in a random sequence[44]. Participants need to determine the presence or absence of facial expressions (anger, disgust, contempt, happiness, fear, sadness, and surprise) with a 9-point rating scale (0 is absence and 9 is presence)[35].

By comparing their rating scores' standard derivation, researchers conclude that women distinguish among the ratings more than men differentiate. This experiment indicates that women can better and quicker to identify emotions than men do. The unequal emotion recognition capacity of male and female probably because female brains are better prepared from born to decode feelings than male[35].

However, the rating students in the study all take part in the experiment as a partial requirement of class. Hence, there may exist a selection bias and spillover effect.

Psychologists conclude that women's and men's brains may interpret emotional signs differently. This conclusion may raise the question of whether women and men express emotion differently. Limited studies have been done in this aspect compared with the analysis of cultural variation. However, some researchers develop research about gender variations in childhood. Maccoby et al. investigate two emotional signals, frustration and fear. Frustration is addressed as tantrums, such as rage or screaming, in reaction to frustrating scenarios. Maccoby and Jacklin identify no apparent gender differences in the display of fear by children. In contrast, they indicate that baby boys and girls are equivalent in their frustration responses, but girls' unpleasant outbursts decrease more than boys with age. As a result, boys (18 months old) report more frustration responses than girls[45].

Chaplin argues that this behavioral pattern may represent girls' tendency to suppress their expression of externalizing feelings, like angry outbursts, since they receive an implicit awareness of the female gender stereotype[46]. This research reveals that gender differences in children's facial behaviors are altered along with age. Although age is not a factor of concern in this thesis, the observation of this study still reveals the existence of facial behavioral variation between genders[46].

Furthermore, the study demonstrated by Kohler et al. indicates some interesting findings in gender differences. Both posed and spontaneous emotional expressions from actors are coded with FACS and scored by professional raters. Only the presence of AU is included during the coding process (e.g., 1 is presence and 0 is absence). For each image, the number of appearances per AU is evaluated, and logistic regression is used to analyze each AU's occurrence rate[41].

Kohler et al.'s work only analyze only four emotions, which are happy, sad, anger and fear, and another two basic emotions, surprise and disgust, are ignored since Kohler et al. suggest that surprise's valence is largely dependent on the trigger, and thus it can be any other emotions. Valence is a dimension of emotion that reflects a feeling's level of pleasure[47]. Besides, disgust isn't analyzed because Kohler et al. believe it isn't a pure emotion but rather a blend of other basic feelings[41].

The result shows no difference in facial expressions posed by male and female in the degree of AU occurrence. Thus, there is no difference in the facial configuration between genders. Besides, this study also indicates that there may be gender differences in facial expression intensity. For example, researchers suggest that in a male's sad face, mouth opening, associated with AU26 (jaw drop), is more usual. In addition, Kohler et al. also

Table 2.4: Uniquely Present Action Units in 4 Emotions

Emotion	**AU**
Happy	6, 12
Sad	17
Anger	9, 16
Fear	5, 20

examine key AUs, which are uniquely present in the four emotions, and the result is shown in the table 2.4[41].

Kohler et al.'s observation of 4 emotions' key AU is consistent with other facial configurations' studies[19][48][41]. Their finding indicates that women and men convey happy, sad, angry and fearful expressions in the same way while the intensity of facial muscle movement may differ. However, this study doesn't examine the intensity of each AU since it only documents the presence of AU without its intensity information. Besides, although researchers exclude surprise and disgust from the analysis due to the assumption that these two emotions are not isolated from other expressions, it is still meaningful to explore the characteristic AU of these two emotions since they have "unique physiological and neural profiles"[49].

Chapter 3

Methodology

3.1 Introduction

The chapter 2 indicates the facial configuration of each basic emotion is diverse with respect to cultural group and gender. Thus, identity the variability in facial behavior is crucial for the emotion recognition system. To deriving the study of emotion characteristics, two datasets that capture Caucasian and East Asian facial expressions are introduced in section 3.2, which includes the data distribution (e.g., gender and emotion categories) and data screening process (e.g., ethnicity and criteria).

In cultural accent study, section 3.3, the variation in facial expression is determined by a logit regression. The independent variable (AU) in the regression is extracted from the facial expression image. Thus, from the regression result, the specific cultural-related pattern is revealed. The section 3.3 also presents the details of AU occurrence extraction and the setup of logit regression

Another major component in this thesis is gender variation. Since the gender variation is reflected in AU intensity, this study constructed four group average faces of male and female in Caucasian and Asian separately. From each average face, the key AU intensity is determined based on related landmarks displacement from neutral face to emotional face[50][9]. The criteria of AU intensity evaluation is describe in section 3.4. By comparing the AU intensity of average female face and average male face, some AUs are considered as gender-specific patterns. To further examine whether the proposed gender-specific patterns are significant, a summary statics of AU intensity of each facial image are performed.

3.2 Dataset

3.2.1 Caucasian Facial Expressions Dataset

The Caucasian facial expression's dataset used is CK+. Before introducing CK+ dataset, CK dataset have to be discussed firstly since it is the foundation of CK+ dataset[51]. CK is a facial expression dataset proposed by Kanade et al. It is a commonly used testing grounds for the development of facial expression recognition algorithm (e.g., test, evaluation, etc.)[52][53]. CK contains image sequences of facial expressions with seven emotional labels, including happy, sad, anger, disgust, contempt, surprise, fear, and neutral. The facial responses of this dataset are captured from 210 male and female adults, including European American (81%), African Americans (13%), and some other groups (6%). Subjects perform 23 facial displays about single AUs and combinational AUs with instruction from an experimenter. Each facial display shows dynamic movements of facial muscles, from the neutral position to the activation position. Thus, 486 sequences from 97 subjects are coded with FACS and have AUs labelled[51][4].

Figure 3.1: Example of facial expressions from CK and CK+ datasets. Images on top are from CK while bottom are from CK+. Example of emotions are disgust (AU 1+4+15+17), happy (AU 6+12+25), surprise (AU 1+2+5+25+27), fear (AU 1+4+7+20), angry (AU 4+5+15+17), contempt (AU 14,), sadness (AU 1+2+4+15+17) and neutral[4]

Based on CK, Lucy et al. propose CK+ dataset, which includes 593 sequences from 124 subjects (107 image sequences of expressions from 27 subjects are newly added based on CK dataset. Besides, only happy expressions are spontaneous while others are posed

Table 3.1: Criteria of CK+ in Filtering Emotional Expression Images [4]

Emotion	**Criteria**
Angry	AU23 and AU24 must be present in the AU combination
Disgust	Either AU9 or AU10 must be present
Fear	AU combination of AU1+2+4 must be present, unless AU5 is of intensity E then AU4 can be absent
Happy	AU12 must be present
Sadness	Either AU1+4+15 or 11 must be present. An exception is AU6+15
Surprise	Either AU1+2 or 5 must be present and the intensity of AU5 must not be stronger than B
Contempt	AU14 must be present (either unilateral or bilateral)

Note: FACS uses A, B, C, D, E to score AU intensity (e.g., A is very low and E is very high)

expressions.). The image sequences, which begin from the neutral frame to the peak (of emotion) frame that is labelled with AUs, have various duration. Besides, only 327 of the 593 sequences have emotion categories labels (happy, sad, anger, disgust, contempt, surprise, fear, and neutral since researches eliminate those facial images that are not satisfied with the criteria in Table 3.1[4]. The example emotions of CK and CK+ with corresponding AU labels are shown in 3.1[4]. The description of each AU can be found in A.1.

Since this thesis only focus on variation in six basic emotional expression between Caucasian and Asian, contempt images from all subjects and facial images from non-Caucasian in CK+ are eliminated .

3.2.2 Asian Facial Expression Dataset

Despite that, another dataset, TFEID, is also used in the thesis. As an Asian facial expression dataset, it contains facial expression images posed by 20 subjects (10 male and 10 female) from two views (front view and side view), and each subject is asked to perform both strong and weak expressions. Unlike CK+, TFEID dataset only documents the peak frame of emotional expressions of each subject. Besides, each facial expression image is labelled with emotions categories, which is consistent with CK+. However, this dataset has not labelled AU to images[54].

3.3 Cultural Variation

3.3.1 Action Unit Occurrence Detection

An open-source toolkit, Openface, is utilized to extract AUs from facial images[55][56]. This machine learning-based toolkit can examine many facial behaviors, including head pose estimation, gaze direction estimation, AU extraction, and facial landmarks detection. Openface employs HOG to extract facial feathers from images and trained the AU appearance detection[57] in the SEMAINE and BP4D, which contain emotional videos with AU occurrence labels. BP4D dataset contains spontaneous facial expressions from 41 participants (23 women, 18 men) with a various cultural group(Asian, African-American, Hispanic, and Euro-American) and SEMAINE contains 150 spontaneous facial recordings from nearly all Caucasian cultural participants[58][59]. Openface can recognize up to 17 AUs (that are all commonly related to emotional expressions) occurrences. Given that facial images from CK+ and TFEID, the binary data of each AU's appearance in Caucasian and Asian(1 is present while 0 is absent) is generated by Openface.

3.3.2 Regression

The logit regression is adopted to compare AUs' differences across cultures with binary data generated by Openface. The dependent variable, racial status, is coded binary, where 0 represents East Asian and 1 for Caucasian. On the other side, the independent variable covers each AU's appearance. Thus, we assume there is no inter-correlation between observations. However, noting that some respondents have multiple facial images recorded. Therefore, coefficients significance may drop. Even though there is an under-estimation of standard errors, we believe there is no endogenous issue among regression analysis where the over-representation may not lead to bias estimators, which is confirmed by previous researches[5].

3.4 Gender Variation

The emotion contempt is not included in the analysis since it doesn't belong to the basic emotion. The intensity of facial muscle movement is regarded as the displacement of a specific facial feature during emotional expression, which is described in 3.4.2.

Individual AU intensity is extracted from the average women's and men's faces, and the percentage difference is computed to identify the gender-specific intensity variation quantitatively. The AU intensity is considered as significant between genders based on the statistical analysis, which involves all AU intensities extracted from all facial images in datasets.

3.4.1 Average Face

The average faces are generated from CK+ and TFEID's image. Before generating average faces, facial landmarks data of each facial image is required. Facial landmarks represent the contour of the human face. A widely acceptable C++ based library, dlib, is employed to extract facial landmark[60]. This machine learning-based package has reliable performance on facial recognition and face detection jobs. Dlib also gives some well-trained models, including a 68 face landmark model, which is trained on the ibug 300-W dataset[61]. Landmarks of TFEID are extracted while CK+ have presented its images' landmarks, and the position of each landmark is illustrated in fig. C.1.

Algorithm 1: Tranform image

Data: input images from dataset
Result: transformed image array
initialization: convert image into image array;
append arrays to one list, $imageArray$;
append each image's landmark arrays to one list, $landmarkArray$;
count number of image , n;
define size of output image's width and height, w,h;
for *i in range (0, n)* **do**
  $eyeCornerCoordinate = (landmarkArray[i][36], landmarkArray[i][45])$;
  `// extract coordinates of eye corners from landmark array`
  define $outEyeCornerCoordinate$ wrt. output image's size
  Function `Similar transformation(`*eyeCornerCoordinate, outEyeCornerCoordinate*`):`
    compute transformation matrix T of $eyeCornerCoordinate$, $outEyeCornerCoordinate$;
    return T;
  based on T, apply similarity transformation to $imageArray[i]$ and get transformed image, $newImage$;
  $newImageArray = append(newImage)$; `// append each newImage into one list, newImageArray`
  newLandmark = transform (T, landmarkArray[i]) ; `// simililar to image, transform each input image's landmark too.`
  newLandmarkArray = append(newLandmark) ; `// store all new landmark to one list, newLandmarkArray`
end

With the labelled landmarks of each dataset image, the average face images are generated by the algorithms 1 and 2 that are inspired by [62]. The input images are transformed uniformly based on the size of face in images. In this thesis, all dataset images are transformed according to the distance between eye corners. Then, a Delaunay triangulation is performed with landmarks and image boundary points on each dataset image and each triangle is bounded by three specific landmark points. By summing all landmarks coordinates and averaging them, all triangles can be projected to a average face by stretching these triangles.

Algorithm 2: Average face generate

Data: input images from dataset;
newLandmarkArray;
width and height of output average image (w, h)
Result: average face image (output image)
initialization: initialize average landmark points array: averagePoints = zeros(76, 2);
k = len(newImageArray) ; `// store the number of images to be average`
for *i in range (0, k)* **do**
    $dummyPonint = newLandmarkArray[i]$; `// store current transformed image's transformed landmark`
    $dummyPoints = append(boundaryPoints)$; `// append coordinate of boundary points (image's 4 vertexes and 4 midpoints of sides) to the dummy points array`
    averagePoints = averagePoints + dummyPoints/n;
    Function `Delaunay triangulation(`*averagePoints*`):`
        do Delaunary triangulation for average landmark points. Each traingle's is formed by 3 points from landmark array. The indexes of these 3 points are documented
        return *indexArray*;
    outputImage = zeros(h,w,3) ; `// initialize the output image array`
    transfrom triangles of transfromed image ,newImageArray, based on average landmarks (newLandmarkArray) and indexs of triangles's vertexes. Then combine all transformed triangles into a transformed image. Append all transformed images array into a list, *outputImage*;
    outputImage = outputImage/k convert outputImage array back to image (average face)
end

3.4.2 Intensity of Facial Muscle Movement

The intensity of facial muscle is extracted from emotional expressions' average facial expression images. Each set of average face images contain six basic emotion images and one neutral average face. The facial muscle movement is recognized by comparing an emotional face and a neutral face, and the key AU patterns in each emotional expression, which is employed from [1], are described in fig.3.2. The intensity of AU is recognized as the displacement of related facial landmark points. The detailed evaluation of each related AU's intensity is described separately. Besides, the MATLAB code that demonstrates each AU intensity calculated can be found in the

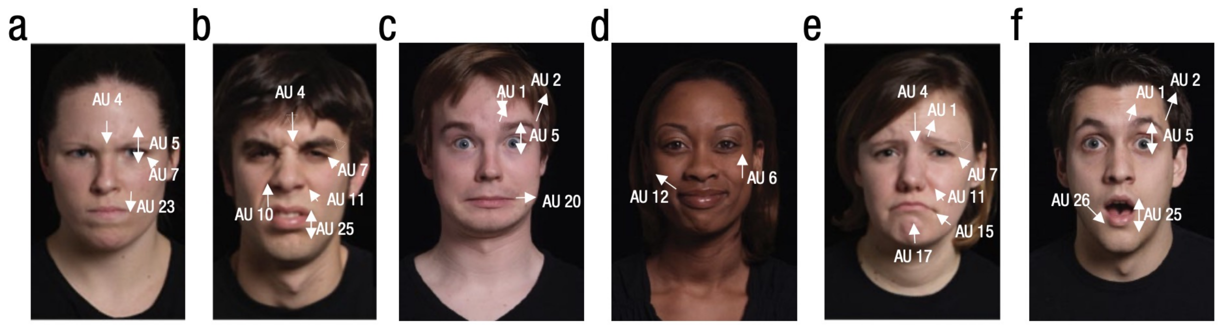

Figure 3.2: Facial action unit ensembles for basic facial expressions. Left to right: anger, disgust, fear, happy, sad, and surprise[1]

AU1

AU1 represents the rise of the inner brow. Fig. C.1 illustrate each facial landmark's position on the human face. The landmarks points with indexes 22 and 23 are related to facial muscles beneath the inner brow[9]. Hence, the intensity of AU1 is represented by the movement of inner eyebrow, which is the landmark 22 and 23's displacement.

Since the inner brow muscle movement is proportional to the eyebrow's width, this displacement is divided by brow's width to eliminate the potential error induced by various width of brow. The percentage difference of inner eyebrow movement in CK+ and TFEID images is recognized as variation in AU1's intensity between Caucasian and Asian.

AU2

AU2 represents the rise of the outer brow. The landmarks points with indexes 18, 19, 26, and 27 are related to AU2. By connecting the landmark 18 and 19, 26 and 27, the line's slope represents the outer brow's shape. Thus, the change in slope between the neutral face and emotional face can be considered as AU2 intensity since the more to raise the outer brow, the more increment in the brow's lateral upward slope. The slope is divided by the brow's width before comparison to rule out the influence of various sizes of brows.

AU4

AU4 occurs when lowering the brow. There can be three scenarios: only the inner brow is lowered, the inner and central brow lowered, or the entire brow is lowered. AU4 may occur along with some other appearance changes, including pushing eyelid downwards, pushing the brows closer to the center, and producing furrow on the brow[9]. Landmarks with indexes 18, 19, 20, 25, 26, 27 are considered as related with AU4 and intensity of AU4 is documented as the movements of these points. The landmarks on the inner brow are not counted since AU1, inner brow raiser, and AU4, brow lowerer, can both presented in emotional expressions, and inner brow movement may be affected by AU1. The sum of related points' displacement is divided by the width of the brow before analysis.

AU5, AU6, and AU7

AU5 reflects the upper lid rise, AU7 is the lids' tightening. AU5 and 7 are addressed together because by only monitoring facial landmarks, it is difficult to discern which one exactly exists since they are both induced by orbicularis oculi's (the muscle surrounds eye) elongation or contraction. Besides, AU6, the rise of the cheek, also contributes to the activation of orbicularis oculi since the cheek's rise will squeeze the eye area. Due to these similarities, these three AUs are recognized as the same method.

Instead of tracking the displacement of landmarks on the eye region, the inverse aspect ratio of the eye represents AU5, 6 and AU7 intensity. The change of the ratio between emotional expression and neutral expression demonstrates is used to evaluated muscle movements.

AU10

AU10 depicts the rise of the upper lip. It demonstrates that the lip's center rises, and the corner of the lip rises too but not as much as the lip's center does. Hence, the intensity of AU10 is recorded by tracking the movement of the 52nd landmark, and the 34th landmarks is used as a reference. The distance of philtrum (which is the indentation between upper lip and nose and demonstrate the length between 34th and 52nd landmark) of the neutral face is regarded as AU10's neutral position. Hence, dividing the change of philtrum's length in the emotional face by its original length in the neutral face, the result can be considered as AU10's intensity.

AU11

AU11 refers to the deepening of the nasolabial furrow. The muscular basis of AU11's appearance has not been investigated completely. Ekman et al. consider AU11 is correlated with the action of muscles in the lower cheekbone and the attached upper lip's regions[9]. Thus, it is difficult to distinguish it from other AUs that are also controlled by the same muscle group (e.g., AU10, the rise of upper lip, AU13, sharp pulling of mouth corner).

AU11 can lead to some changes in appearance, including pulling the skin around the nasolabial furrow upwards, deepening the nasolabial furrow, and raising the upper lip slightly[9]. Hence, the occurrence of AU11 may involve the happening of AU10. The AU11 intensity is considered as dividing the change in the width of nostrils (the distance between 32nd and 36th landmark) in the emotional face by the width of nostrils in the neutral face, instead of considering philtrum to eliminate the effect of AU10.

AU12, AU15, and AU20

AU12, AU13, AU15, and AU20 are discussed together since they all describe the change in the appearance of the mouth region. AU12, lip corner puller, appears when lifting the cheekbone and attached muscle circles mouth corner. It pushes the lip corner up in an oblique direction and produces a curved shape of the mouth[9].

AU13, lip corner puller, also produces a curve-shaped mouth and pulls lip corner towards the cheekbone, which is very similar to AU12. The angle of lip brought by AU13 is sharper than AU12[9]. The difference between these two AUs is subtle, but AU13 is not a key AU in facial expression, and thus, there is no need to classify them in this study.

AU15 indicates the depressor of the lip corner. It pulls down the lip corner and stretches the lip corner. Besides, AU20 also stretches the lip corner horizontally. The difference between AU15 and AU20 is the resultant shape of the lip. The lip corner's shape produced by AU15 is angled down, while AU20 may produce a rise or down of the lip corner, but the main action is horizontal stretching[9].

The intensities of these AUs, related with the mouth, are identified as the change in month's width divided by the month's width in the neutral face. As discussed above, some of these AUs also involves the change of lip corner in the vertical direction. This change is neglected since it is subtle compared with the horizontal change.

AU23

AU23 represents the tightener of lips. It is induced by the contract of muscle that orbits the mouth. When AU23 present, the lips are compressed, and red parts are concealed. AU23 may be mistaken to AU24, lip presser. The difference between these two AUs is AU23 can present only in either top lip or bottom lip. Since AU23 is mostly associated with the narrowing of lips, its intensity is interpreted as the change of lips' thickness in emotional expression dividing with the neutral face's lip's thickness.

AU25 and AU26

AU25, lips part, and AU26, jaw drop, are considered co-related since they describe the mouth's opening. AU25 emphasizes the separating of lips, which may lead to exposure of inner lips or teeth, and AU26 specifies how much the jaw has fallen though the parting of lips always brings out jaw's dropping.

The intensity of AU25 is demonstrated by the change in inverse aspect ratio of mouth in emotional face divided by it in the neutral face. Besides, AU26's intensity is shown by dividing the variation of distance between jaw to the eyes' center distance in emotional expression and the neutral expression to neutral expression.

Chapter 4

Result and Discussion: Impact of Culture

4.1 General Discussion

The table 4.1, result of logit regression, shows some racial differences in facial expression. Some AUs are regarded as significant among two cultures according to the corresponding p-value. Besides, table 4.3 also lists the AUs that are highly related with emotional expression. Given that, table 4.2 summarizes the key AU that are significant in the proposed thermos and the logit regression result and indicates the racial bias.

Table 4.1: Logit Regression Result with Racial Status as Dependent Variable

	Dependent variable:					
	Cultural Group					
	Anger	Disgust	Fear	Happy	Sad	Surprise
AU01	1.449***	0.051	−0.017	−0.245	−0.595	0.311
	(0.536)	(0.472)	(0.578)	(0.364)	(0.457)	(0.446)
AU02	−3.448***	−1.045**	−2.074***	−1.560***	0.229	−0.804*
	(0.621)	(0.507)	(0.706)	(0.393)	(0.383)	(0.483)
AU04	−1.895***	−0.367	−4.335***	−1.213***	−0.319	−0.304
	(0.511)	(0.500)	(0.738)	(0.387)	(0.456)	(0.423)
AU05	0.299	0.294	2.840***	1.548***	2.120***	1.594***
	(0.499)	(0.651)	(0.676)	(0.416)	(0.458)	(0.339)
AU06	2.146**	0.366	1.773**	−1.615**	−4.827***	15.117
	(0.835)	(0.650)	(0.842)	(0.804)	(1.284)	(1,528.206)
AU07	1.580***	1.537***	3.465***	1.992***	2.400***	4.140***
	(0.477)	(0.589)	(0.824)	(0.434)	(0.416)	(1.028)
AU09	3.513***	3.171***	2.961***	3.703***	19.262	17.286
	(0.765)	(0.766)	(0.895)	(0.539)	(1,369.577)	(696.318)
AU10	−6.440***	−5.010***	−3.150***	−3.152***	−33.559	−2.803***
	(1.098)	(0.874)	(0.968)	(0.645)	(2,559.100)	(1.068)

Table 4.1: Logit Regression Result with Racial Status as Dependent Variable

	Dependent variable:					
	Cultural Group					
	Anger	Disgust	Fear	Happy	Sad	Surprise
AU12	2.265	−0.012	1.115	0.059	19.109	−1.076**
	(14.705)	(0.650)	(0.679)	(0.830)	(2,467.182)	(0.503)
AU14	−0.760	2.240***	1.176*	3.116***	−0.470	4.641***
	(0.470)	(0.577)	(0.646)	(0.535)	(0.671)	(1.412)
AU15	−2.952***	−3.829***	−2.439***	−1.968***	−0.808	−0.700***
	(0.733)	(0.602)	(0.637)	(0.358)	(0.552)	(0.271)
AU17	0.958**	0.681	0.489	1.253*	1.680***	1.702***
	(0.431)	(0.439)	(0.916)	(0.644)	(0.349)	(0.475)
AU20	0.714	−0.504	4.078***	0.501	0.251	0.260
	(0.472)	(0.426)	(0.820)	(0.342)	(0.359)	(0.292)
AU23	−0.914**	−0.509	−2.305***	−0.689*	0.075	−0.021
	(0.419)	(0.433)	(0.587)	(0.357)	(0.379)	(0.269)
AU25	−18.421	−3.735***	−1.952***	1.105**	−0.824	0.333
	(799.088)	(0.718)	(0.601)	(0.430)	(0.609)	(0.299)
AU26	−0.978**	−0.895**	1.171**	−0.009	−1.205***	0.110

Table 4.1: Logit Regression Result with Racial Status as Dependent Variable

	Dependent variable:					
	Cultural Group					
	Anger	Disgust	Fear	Happy	Sad	Surprise
	(0.416)	(0.417)	(0.525)	(0.396)	(0.371)	(0.382)
AU28	2.408***	−18.680	4.016***	13.612	0.851	−0.775
	(0.634)	(991.505)	(0.948)	(632.425)	(0.545)	(0.575)
AU45	2.279***	2.615***	3.247***	1.616***	1.103***	2.285***
	(0.443)	(0.464)	(0.808)	(0.339)	(0.355)	(0.413)
Constant	3.287***	2.852***	−0.945	0.528	−0.269	0.390
	(0.835)	(0.731)	(1.001)	(0.506)	(0.741)	(0.538)
Observations	847	779	499	1,129	487	1,160
Log Likelihood	−103.187	−105.903	−89.077	−171.041	−133.953	−254.705
Akaike Inf. Crit.	244.375	249.805	216.153	380.081	305.907	547.410

Note: *p<0.1; **p<0.05; ***p<0.01

Table 4.2: Racial Preference Action Unit

	Caucasian	**East Asian**
Anger	AU7	AU4, AU23
Disgust	AU9	AU10, AU15, AU25, AU26
Fear	AU5, AU7, AU20, AU26	AU2, AU4, AU25
Happy	AU25	AU6
Sad	AU5, AU17	AU26
Surprise	AU5	AU2, AU26

Table 4.3: Some Proposed Facial Configuration Coded with Facial Action Coding System[1]

Emotion	**Common AU**	**Darwin**	**Matsumoto et al.**	**Ekman et al.**
Anger	4, 5	4 + 5 + 24 + 38	4 + 5 or 7 + 22 + 23 + 24	4 + 5 + 7 + 23
Disgust		10 + 16 + 22 + 25 or 26	9 or 10, 25 or 26	9 + 15 + 16
Fear	1, 2, 5, 20	1 + 2 + 5 + 20	1 + 2 + 4 + 5 + 20, 25 or 26	1 + 2 + 4 + 5 + 7 + 20 + 26
Happy	6, 12	6 + 12	6 + 12	6 + 12
Sad	1	1 + 15	1 + 15, 4, 17	1 + 4 + 5
Surprise	1, 2, 5, 26	1 + 2 + 5 + 25 or 26	1 + 2 + 5 + 25 or 26	1 + 2 + 5 + 26

It is observed that some significant AUs in the regression table are not regarded as key AU by the proposed facial configuration theorems in table 4.3. For instance, AU45 is not listed among theorems. However, it is positive and significant among all emotion categories. Thus, by detecting eyes are closed, which is AU45, it is more likely that the respondents belong to Caucasian than East Asians. However, this variation may not be caused by racial differences. Keep in mind that Openface's initial training set contains a huge proportion of Caucasian[56][58][59], the generalizing predicting function towards East Asians may be doubted. By looking at the summary statistics, only around 25% of East Asian samples have a positive AU45 while it rises to 50% for Caucasian groups. Furthermore, the initial report from Openface indicates the prediction success rate on AU45 is quite low compare to other AUs [55]. Therefore, the conclusion that there is a racial expression difference on AU45 can not be reached.

The same concern may go to AU9, nose wrinkle, where all significant estimators are positive. The two-sample t-test for AU9 presences between two races is significant. This suggests a potential AU capturing difference across race. In that sense, there is a data collecting difference in facial recognition from Openface.

Despite the consistent impact due to the Openface collection, some other racial differences that are not listed in theorems may exist. AU26, jaw-dropping, may give different meaning in different cultures. For instance, jaw-dropping may hint at the sadness in the

East Asian background while it correlates to fear in Caucasion. This finding aligns with Jack et al.'s previous research[3]. They conclude that East Asian facial expression contains a lot of AU near the mouth in the sadness expression, which is not identical to Caucasian.

In the following sections, the racial bias of each emotion category is discussed. This thesis majorly focuses on the AUs in table 4.2, which are both highlighted in the regression table and proposed theorems, since these AUs are commonly used to interpret emotions.

4.2 Anger

In table 4.2, AU4 and AU23, brow lower and lip tightener, are more common in East Asian backgrounds, while AU7, lid tightener, is more common in Caucasian. This observation suggests that both Caucasian and East Asian express anger by contracting muscles around the eyes, and this activity is more obvious among Caucasian.

This result is not perfectly aligning with Cordaro et al.'s observation in table 2.2[5]. However, this result is parallel to Jack et al.'s conclusion that there is limited racial difference in anger expression and East Asian tend to release the anger by tightening lips[3].

4.3 Disgust

For disgust, most of the proposed theorems hold equally well between groups. This means from Openface's detection, two disgust faces that are from both East Asian and Caucasian groups will be assigned to the same emotion category. For the East Asian group, the lip-corner depressor is more common than the Caucasian.

However, there is no common pattern in between our results in table 4.2 and Cardaro et al.'s observation in table 2.2[5]. Potential reasons for that may seem due to the limited facial finding that is pointed at the table 2.2. Most of the AU differences in table 2.2 lies in gestures and facial rotations. On the other hand side, this result close to the Jack et al.'s finding[3], which suggests that East Asian's lid and lip activity, like AU2 and AU10, are more frequent than the Caucasian. The nose region activities, AU9, are similar to Jack et al. and Matsumoto et al.'s pattern in fig. 2.2 and table 4.3, which indicate that Caucasian muscles in the middle face is more active in disgust expression.[3][1][63].

For the mouth region, both Darwin and Matsumoto et al. indicate there are either AU25 or AU26 associated[63][6]. From the result in table 2.2, the East Asian group presents a relatively higher chance by having such AU detection.

4.4 Fear

In the category of fear, different AU behaviors are observed. From table 4.2, East Asians are more often to present a brow lower while Caucasians have more eye tightening. This is suggested by AU4 and AU7. Given that two AUs are also the crucial AU in table 4.3, it is concluded that even within Ekman's initial statement, certain AUs may be more frequent and common to present while others are relatively rare.

There aren't that many differences that are pointed by either table 2.2 or jack's result[3] in fig. 2.2. Despite the dynamic pattern (e.g., eye motion) that this study cannot reflect, the AU25, lips part, is significant among East Asians. Cordaro et al. indicate that AU25 is most common in China, which is similar to the observation in table 4.2 [5]. In that sense, there may be a racial preference in AU expression given the same potential chance discussed by Matsumoto et al. [63]. For instance, AU25 is more preferred by the East Asian group.

Besides, from the regression results in table 4.1, there is a similar trend in the sign of estimators between anger and fear. However, the magnitude of fear is greater than anger among significant estimators. Given that fear is less dominant emotion than anger[64], it is concluded that certain trends are more observable within the same racial group due to the lack of control in fear expression. For instance, anger, a high-dominance emotion, may be impacted by the personal characters.

4.5 Happy

As table 4.2 shows, East Asian happy faces are more correlated with AU6, cheek raiser. On the other hand, more AU25, lips apart, in Caucasian are observed. However, table 4.3 suggests that the crucial AU in happy expression is AU12, lip corner puller, instead of AU25, lips apart. Therefore, lips apart may be considered a more obvious action compare to lip corner puller, AU12, in AU detecting. By reaching a similar status among AU12, the more frequent AU25 among Caucasians may lead to another conclusion. When asked to present a certain emotion, East Asian tend to present a face that will consider less intensive by White Caucasian.

There is an interesting pattern near nose regions in table 4.1. AU9, the wrinkle, is not a crucial AU in table 4.3, and it is more observable among the Caucasian group. Hence, there is a likely chance that East Asians may present less nose wrinkle. This pattern can be explained by the age difference between datasets. For CK+, the original respondents' age ranges from 18 to 50. On the other hand, the East Asian group in TFEID is majorly young people with narrow age gaps. Thus, the age difference may over-estimate the AU 9's actual difference.

4.6 Sad

For the sad category, White Caucasian fit the proposed facial configuration model better than East Asians. AU5 and AU17, two crucial AU in table 4.3, are both more observable among Caucasian. Besides, as table 2.2 shows, AU17 is also a CVP in Caucasian. Therefore, it is concluded that AU17 is a racial preference in sad expression. The table 4.2 also indicates that most of the CVPs in East Asian are related to mouth and jaw, which is consistent with the finding in table 4.2 and fig. 2.2. Hence, it is also concluded that East Asian respondents have more lower-face activities than Caucasians during sadness[3]. East Asian are observed to display AU26, jaw-dropping more frequent than Caucasian. Simultaneously, White Caucasian have more lids activities, including AU5 and 7, which are not common among East Asian.

Despite that, it is notable that there are fewer sad figures within the initial dataset than other emotions. Hence, there will be a challenge that the existing data is too low to represent the group.

4.7 Surprise

There are some minor differences between racial groups in the eyes region. As table 4.2 shows, Caucasian is more likely to raise the upper lid while East Asian prefer to raise the outer brow. Besides, East Asian also tend to drop the jaws in surprise expressions. However, this observation is not consistent with Cordaro et al. and Jack et al.'s works[5][3]. It is interesting that the CVP in Caucasian surprise expression, AU4(brow lowerer), are not significant among Caucasian in table 4.1. Instead, the AU2(outer brow raiser), which is opposite to AU4, are significant among East Asian. Given that the AU detection model is majorly trained with Caucasian facial expression[55], it is likely that such AUs are mistaken among East Asian.

Despite that, there is a similarity among coefficients between surprise and happy. Another robustness check is constructed to decompose the reason behind it. The other two logit regression are performed within the same racial group between two emotions in table D.1. The result indicates that the East Asian group's coefficients are similar between happy and surprise while they have a different pattern for the White Caucasian. Therefore, it will be really hard for the model to identify the happy and surprise in East Asian faces due to the high similarity. [41].

4.8 Limit

4.8.1 Logit Regression Model

Due to the correlation of facial landmarks, the correlation may challenge the regression model's internal validation. For instance, AU25 describes the open of mouth while AU26 demonstrates the drop of the jaw. These two actions are likely showed in pairs. In the regression model, if two independent variables are highly correlated while one is important for the facial interpretation, the regression coefficients of both tend to be significant. Therefore, the standard error of the not crucial term will be under-estimate. However, without proper facial frameworks, it is impossible to select the correct specification. Therefore, there should be more researches in understanding the landmark influences

4.8.2 Reliability of AU detection

Another limitation of this thesis is the reliability of AU occurrence detection result. Openface tests the performance of AU detection on SEMAINE and BP4D and the accuracy of each AU occurrence is uneven. For example, Openface recognises AU10 with 84% accuracy while recognises AU10 with only 33% accuracy[56]. Hence, the inaccurate AU capture may cause a further measurement error issue. Since the initial Openface description does not test the causal component for the capture error, the error may be possible to be decomposed into two categories, random and non-random. If the capture of Openface has a random error component, then the standard error estimated from the regression may be larger than the real one. Therefore, the random error component will not influence the magnitude of the coefficients. A more severe problem may arise if the error component is non-random. For example, there may be a non-random error correlated with some AU characters and the error is correlated with the AU's intensity. Thus, the more intense AU is more likely to be detected. Then, the coefficient may be underestimated, while the significance should not change. In conclusion, the potential measurement error shall not influence results from the previous section.

Besides, the Openface package itself may face an external validation issue. For the training base of the Openface, it includes SEMAINE and BP4D which are mainly Caucasian facial expressions. Therefore, one important assumption is that the change and movements of AU should be consistent across all races. So far, such literature is unavailable. The inconsistent movements of AUs may cause similar measurement error described above. That means the Asian group may face a larger measurement error. The table 4.1 compares the facial configuration between two cultural group. It is noticed that there are only minimal changes within the Asian group. Besides the cultural influences, the potential measurement error may also shed out the difference.

4.9 Summary

This thesis extracts 18 AU from Caucasian and East Asian facial expressions and conducts a logit regression to analyze emotional expression variation. The result shows that Caucasian and East Asian express most emotions (except anger) differently, which verifies the findings in [3] and [5].

Besides the cultural accent, this thesis discloses that the same AU may convey different emotional meanings in Caucasian and East Asian. For example, Asian drop the jaw in a sad expression while Caucasian present it in fear expression. In addition, Caucasian and Asian pose the same emotion by activating various facial muscles, which aligns with the proposed theory in [3][5]. Besides, this thesis finds that East Asian facial expression is highly similar in surprise and happy, whereas Caucasian are not. It reflects that East Asian facial expression is harder to be interpreted than Caucasian.

Chapter 5

Result and Discussion: Impact of Gender

5.1 Gender Variation

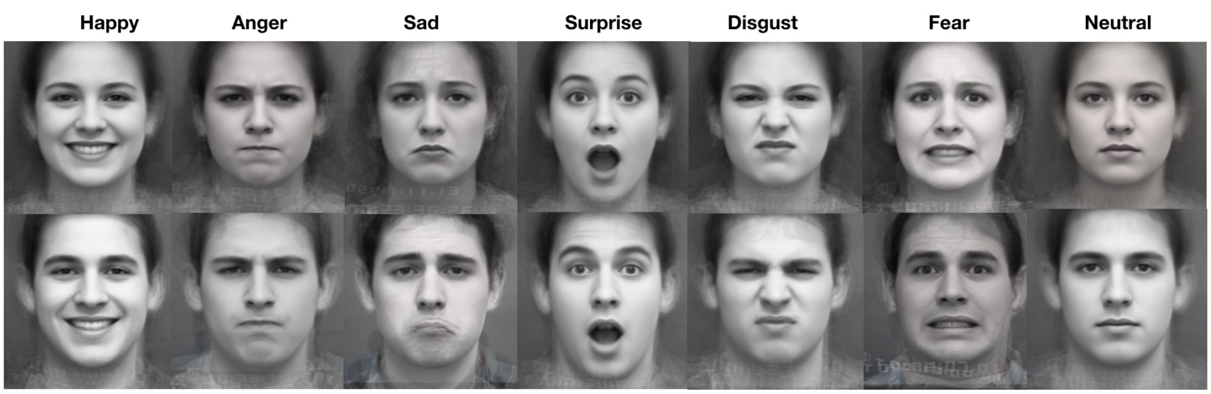

Figure 5.1: Average Caucasian Male and female a face generated from CK+

The fig. 5.1 and fig. 5.2 illustrate the average Caucasian and East Asian facial expressions, and table 5.1 compares the percentage difference of extracted AU intensity from average face. However, even though some percentage difference of AUs intensity are quite large, it can be concluded that AU is significant. Therefore, two summary statics of AU intensity in each facial expression images are conducted and result can be found in the table 5.2 and table 5.3. The finding indicates that there is not much gender difference in

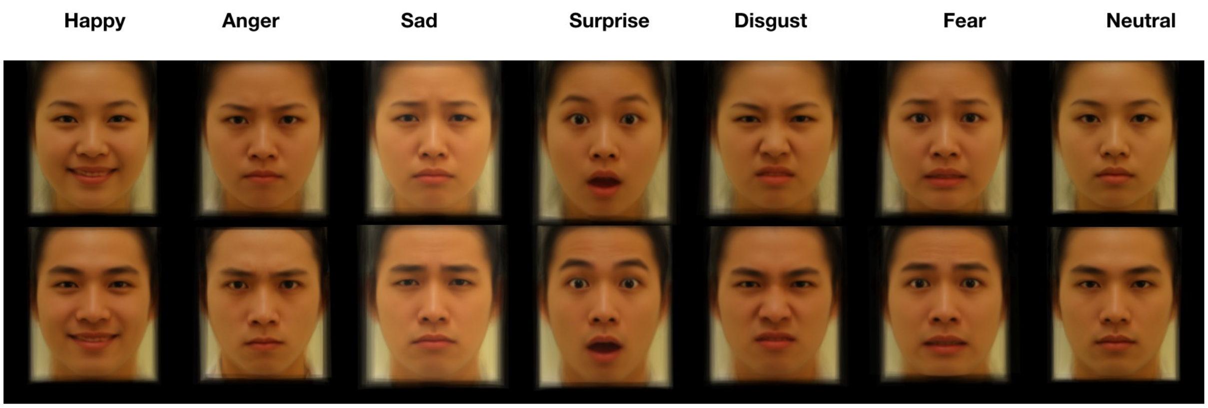

Figure 5.2: Average East Asian male and female face generated from TFEID

AU intensity within the same racial group, especially in Caucasian. In Caucasian's emotional expression, there is the only gender difference in disgust and surprise, while gender difference is more significant in East Asian's emotional expression. This observation is consistent with the assumption that gender variation is highly associated with social roles, and gender discrimination reshapes the facial expression[22]. Less gender variation is observed within Western Caucasians since there is less gender inequality in Western society.

5.1.1 East Asian

In anger, there are significant gaps in AU4 and 5 within East Asian, which is shown in table 5.2. The AU4, brow lowerer, is reported more intense in East Asian women than men while AU5 and 7, upper lid raiser and lid tightener, are more intense in Asian men. From the average face of East Asian anger expression in fig. 5.3, the percent differences of AU4 and 5&7 intensities (AU5 and 7 combined since they are controlled by the same muscle group) are 54.55% and 145.45%. Anger, a powerful emotional expression, is usually suppressed by women since anger is incompatible with feminine characteristics, and the AU intensity in women's anger expression should be less intense than men's[65][66]. However, the finding in table 5.2 indicates that East Asian women are more expressive in the brow region, which not aligns to [66][65]. Given that women show more facial expressions than males in response to stimulus[67], the female subjects in TFEID may exaggerate their expressions during dataset collection and resultant higher AU intensity in the brow region.

In addition, in fear expression, the East Asian men's AU5 (upper lid raiser) intensity is higher than women, and fig. 5.4 shows the percent difference of AU5 intensity in East Asian

Table 5.1: Action unit intensity comparison on two genders Caucasian and East Asian average face

		Anger			**Disgust**					**Fear**		
		AU4	AU5	AU23	AU4	AU7	AU10	AU11	AU1	AU2	AU5	AU20
East Asian	Men	0.08	0.19	0.19	0.30	0.19	0.18	0.14	0.10	5.26	0.30	0.08
	Women	0.14	0.03	0.17	0.38	0.23	0.08	0.11	0.06	2.92	0.21	0.11
	percentage difference	0.55	1.45	0.11	0.24	0.19	0.77	0.24	0.50	0.57	0.35	0.32
Caucasian	Men	0.26	0.18	0.19	0.32	0.53	0.23	0.14	0.07	7.87	0.10	0.25
	Women	0.50	0.16	0.42	0.44	0.40	0.15	0.06	0.03	4.11	0.09	0.28
	percentage difference	0.63	0.12	0.75	0.32	0.28	0.42	0.80	0.80	0.63	0.11	0.11
		Happy		**Sad**					**Surprise**			
		AU6	AU12	AU4	AU7	AU11	AU15	AU1	AU2	AU5	AU25	AU26
East Asian	Men	0.20	0.29	0.05	0.10	0.05	0.04	0.15	11.87	0.43	20.50	0.09
	Women	0.14	0.34	0.12	0.12	0.04	0.05	0.12	7.94	0.42	12.00	0.06
	percentage difference	0.35	0.16	0.82	0.18	0.22	0.22	0.22	0.40	0.02	0.52	0.40
Caucasian	Men	0.28	0.39	0.26	0.06	0.05	0.05	0.15	10.76	0.29	20.33	0.17
	Women	0.27	0.39	0.18	0.06	0.06	0.07	0.15	12.51	0.27	44.54	0.23
	percentage difference	0.04	0.00	0.36	0.00	0.18	0.33	0.00	0.15	0.07	0.75	0.30

Table 5.2: Summary Statics of AU Intensity in Anger, Disgust, and Fear within East Asian and Caucasian

			Anger			**Disgust**					**Fear**			
			AU4	AU5&7	AU23	AU4	AU7	AU10	AU11	AU25	AU1	AU2	AU5	AU20
East Asian	Women	Mean	0.128	0.076	0.175	0.195	0.250	0.163	0.099	0.162	0.097	7.552	0.181	0.103
		STD	0.056	0.058	0.119	0.083	0.149	0.108	0.089	0.115	0.044	4.405	0.221	0.067
		Observation	38	38	38	40	40	40	40	40	40	40	40	40
	Men	Mean	0.102	0.142	0.213	0.204	0.257	0.192	0.122	0.139	0.100	7.334	0.278	0.100
		STD	0.041	0.133	0.142	0.086	0.175	0.139	0.093	0.100	0.038	4.228	0.167	0.093
		Observation	34	34	34	38	38	38	38	38	36	36	36	36
	T test		2.264	-2.659	-1.200	-0.445	-0.178	-1.033	-1.089	0.942	-0.307	0.219	-2.166	0.150
	DF		67.611	44.132	64.696	75.402	72.799	69.775	75.379	75.526	73.886	73.679	71.977	63.172
	p Value		0.027**	0.011**	0.234	0.657	0.860	0.305	0.280	0.349	0.759	0.827	0.034**	0.881
Caucasian	Women	Mean	0.163	0.222	0.281	0.174	0.375	0.175	0.104	0.131	0.064	5.366	0.010	0.209
		STD	0.063	0.141	0.156	0.082	0.127	0.110	0.059	0.115	0.027	2.807	0.141	0.081
		Observation	22.000	22.000	22.000	27.000	27.000	27.000	27.000	27.000	14.000	14.000	14.000	14.000
	Men	Mean	0.148	0.246	0.231	0.190	0.480	0.171	0.113	0.125	0.103	8.468	0.096	0.195
		STD	0.078	0.204	0.158	0.048	0.157	0.115	0.074	0.090	0.062	5.630	0.188	0.084
		Observation	13	13	13	19	19	19	19	19	6	6	6	6
	T test		0.572	-0.374	0.925	-0.816	-2.414	0.139	-0.443	0.173	-1.501	-1.283	-1.004	0.350
	DF		21.302	18.920	25.082	42.741	33.514	37.775	32.916	43.432	5.827	6.095	7.537	9.241
	p Value		0.573	0.713	0.364	0.419	0.021**	0.890	0.661	0.863	0.185	0.246	0.347	0.734

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table 5.3: Summary Statics of AU Intensity in Happy, Sad, and Surprise within East Asian and Caucasian

			Happy		**Sad**					**Surprise**				
			AU6	AU12	AU4	AU7	AU11	AU15	AU17	AU1	AU2	AU5	AU25	AU26
East Asian	Women	Mean	0.173	0.320	0.156	0.141	0.026	0.044	0.066	0.102	8.570	0.318	0.314	0.085
		STD	0.137	0.101	0.064	0.100	0.043	0.039	0.060	0.042	4.068	0.110	0.223	0.070
		Observation	40	40	40	40	40	40	40	36	36	36	36	36
	Men	Mean	0.182	0.297	0.117	0.148	0.014	0.044	0.068	0.124	10.445	0.397	0.352	0.094
		STD	0.138	0.115	0.044	0.112	0.046	0.049	0.057	0.039	4.867	0.180	0.216	0.060
		Observation	38	38	36	36	36	36	36	37	37	37	37	37
	T test		-0.259	0.936	3.140	-0.264	1.121	0.007	-0.134	-2.332	-1.787	-2.265	-0.739	-0.613
	DF		75.756	73.569	69.495	70.695	71.851	66.826	73.771	70.297	69.436	59.910	70.726	68.906
	p Value		0.796	0.352	0.002***	0.793	0.266	0.995	0.894	0.023**	0.078*	0.027**	0.463	0.542
Caucasian	Women	Mean	0.314	0.369	0.111	0.094	-0.012	0.061	0.077	0.134	10.956	0.294	0.657	0.225
		STD	0.133	0.058	0.043	0.093	0.040	0.069	0.068	0.051	4.762	0.245	0.114	0.073
		Observation	37	37	13	13	13	13	13	42	42	42	42	42
	Men	Mean	0.257	0.355	0.110	0.133	0.032	0.087	0.097	0.145	11.670	0.306	0.614	0.195
		STD	0.116	0.097	0.038	0.162	0.064	0.082	0.101	0.049	5.246	0.162	0.078	0.069
		Observation	18	18	7	7	7	7	7	28	28	28	28	28
	T test		1.619	0.566	0.066	-0.591	-1.658	-0.725	-0.480	-0.950	-0.579	-0.246	1.901	1.751
	DF		38.327	23.120	13.944	8.195	8.588	10.591	9.021	59.391	54.071	68.000	67.925	60.321
	p Value		0.114	0.577	0.948	0.570	0.133	0.484	0.643	0.346	0.565	0.807	0.062*	0.085*

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

average fear face is 35.29%. It is interesting that AU5 is also significant in table 4.1, which indicates that Caucasian tend to display this AU more frequent than East Asian. Thus, there is a heterogeneity issue within the East Asian group. They tend to express AU5 less common than Caucasian groups. However, for the sub-male group that presents such AU, the intensity shall be higher. This interesting pattern may cause some prediction issues. For instance, the initial training model may not capture such AU as a robust variable although it is highly correlated with fear emotion for a specific sub-group.

In sad expression, East Asian women are more expressive than men, especially in AU4, brow lowerer. The fig. 5.5 shows the percent difference of AU4 intensity in East Asian average sad face is 82.35%. This result is consistent with the previous finding that women score higher in sad than men with differential emotions scale[12].

In the surprise, Asian men express most AUs more intense than women. The fig. 5.6 shows the percent difference of such AU, including AU1, 2, and 5, in East Asian average surprise face are 22.22%, 39.68%, and 2.35% separately. This finding is different from [67], which states that men are less expressive than women in surprise expressions. The potential reason for that may be due to the lack of Asian literature. The study groups in [67] are mainly Caucasians, which is consistent with our finding in the lower part of the summary statistics, table 5.3, which proves that Caucasian woman surprise expression is more obvious than men and the Asian male group presents a reverse correlation between AU intensity and gender in surprise expression.

Figure 5.3: Average anger face of East Asian with annotation of gender-specific expressive action unit

5.1.2 Caucasian

Unlike findings from East Asian facial expressions, the summary statistics do not find many significant gender differences in the Caucasian group. The surprise emotion aligns with past findings in [67] that female is more expressive in posing surprise expression, and fig. 5.7 illustrates the percent differences of AU25 and 26 intensities in Caucasian surprise expression are 74.64% and 30% separately.

Besides, for the disgust emotion, the male has a higher average AU7 intensity and the percent difference of AU7 intensity in average Caucasian disgust face is 27.96%, which is showed in fig. 5.8. This finding suggests that the muscle activity near eyes is stronger in male groups than female groups. Given that, this pattern may help in understanding the past literature of disgust interpretation. [68] states that male disgust faces are more interpretable than females. In that sense, the higher intensities for such AU can help to perceive, understand and predict the ongoing emotion.

5.2 Limitation

Facial expressions of CK+ dataset are the combination of posed emotional expressions and spontaneous expressions. As mentioned in section 2.3, the generalizability of posed facial expression is questionable sine the posed expressions from subjects are artificial[5]. Besides, all expression images are manually coded with FACS by the observer. Thus, the emotion label is the judgment from observer instead of subject's self report. The reliability of the

Figure 5.4: Average fear face of East Asian with annotation of gender-specific expressive AU

emotion categories labels is fully depended on observer[42]. In consequence, the emotion labels may be not well validated[4].

In addition, as specified in Ekman's theorem[1], CK+ filters out multiple images due to the inconsistent AU combinations[4]. The table 5.4 concludes the number of subjects and images within the dataset after the sorting. Given a dataset with even observation across different emotion categories, the remaining figures in sad section are way lower than surprise. Thus, it seems that empirical observations indicate surprise emotions align with the theorem the most. Due to the imbalance of data depletion, the data selection process may cause inconsistent training outcomes. In other words, a trained model that adopts observed cultural and gender variations in this thesis may have different performances between emotions in prediction. The training outcome may not provide a robust prediction of sad emotion since some special sad faces are not included within the dataset.

The same concerns may also arise in the gender context. According to the initial description of CK+, it is said that the initial gender distribution is 30% male for the initial data recording. The table 5.4 shows that the remaining male proportion increased. This phenomenon hints that there can be a gender difference in facial expression, while male respondents express similar patterns according to Ekman's theorem[5].

Besides, all non-Caucasian facial expressions are removed from visual distinguishment. There is a possibility of measurement error during data sorting. However, there is no clear evidence that such sorting is correlated with facial expression. Thus, it can be conclude that this sorting process might not cause further estimation problems.

Averagely, about 30% of female subjects from CK+ are not included in the analysis,

Figure 5.5: Average sad face of East Asian with annotation of gender-specific expressive action unit

while only 14% of males are removed. That is caused by uneven racial distribution from the initial CK+ data collection. Since the sorted data is relatively even across the six basic emotions, there is no dominant belief that certain emotion is indistinguishable.

Unlike CK+, the Asian facial expression dataset, TFEID, is not associated with a detailed document. Hence, the procedure of facial recording is unknown. Besides, the filter criteria of emotional expressions are unspecified. Researches have not compared the accuracy of emotion classification in TFEID with other benchmarks. Therefore, the quality of facial images in TFEID can't be identified.

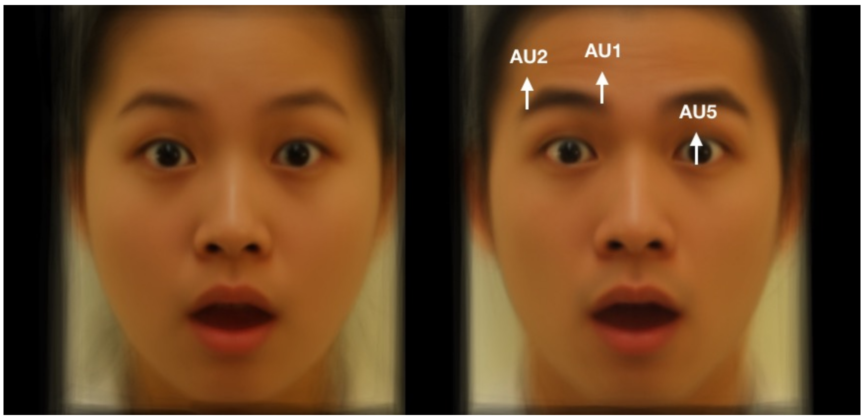

Figure 5.6: Average surprise face of East Asian with annotation of gender-specific expressive AU

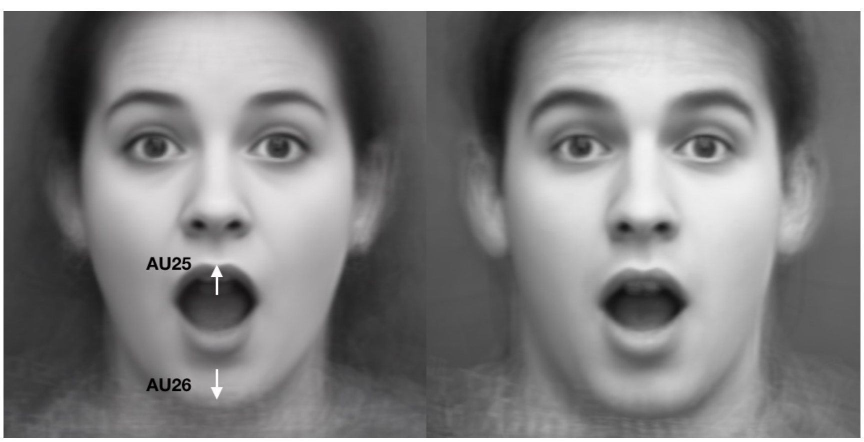

Figure 5.7: Average surprise face of Caucasian with annotation of gender-specific expressive action unit

Figure 5.8: Average disgust face of Caucasian with annotation of gender-specific expressive action unit

Table 5.4: Summary Statics of CK+ dataset

	Selected CK+				**Orignial CK+**			
	Men		**Women**		**Men**		**Women**	
Emotion	**Number of Subjects**	**Number of Images**	**Number of Subjects**	**Number of Images**	**Number of Subjects**	**Number of Images**	**Number of Subjects**	**Number of Images**
Anger	13	270	22	431	14	292	30	659
Disgust	19	283	27	367	20	292	39	510
Fear	6	128	14	239	7	143	18	383
Happy	18	345	37	664	20	357	49	867
Sad	7	150	13	200	9	185	18	294
Surprise	28	409	42	637	29	424	54	781
Total	32	1585	52	2538	37	1693	72	3494

Note: multiple respondents have more than 1 emotion record.

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5.3 Summary

This thesis finds the gender specific AU intensity pattern in Caucasian and East Asian since limited researches has been conducted in this subject. Despite that, Kohler et al. suggests that gender differences may related to facial expression intensity[41]. Thus, this thesis focus on investigating the AU intensity differences between two genders. Only limited variation is discovered among Caucasian compared with East Asian. This pattern can be explained by different levels of gender equality: inborn facial expressions are reshaped by gender stereotype[46].

Chapter 6

Conclusion and Future Work

6.1 Conclusion

Socialization and gender stereotypes reshape the inborn facial expressions. Some works have confirmed that there is a culturally specific facial configuration in Caucasian and East Asian. This thesis utilizes logit regression to examine a subset of AUs related to six basic emotions (anger, disgust, fear, happy, sad, and surprise) in Caucasian and Asian facial expressions. Most of the observations align with previous studies. Besides, this thesis also explores the gender variation in facial expressions. The present investigations suggest that: :

- There is a similarity between East Asian surprise and happy expression. This interesting pattern may be correlated with stimuli material in TFEID since the valence of surprise depends on the triggering stimuli[41].
- Caucasian female is generally more expressive than male in surprise expression, while opposite to East Asian that Asian male is more expressive.
- Gender variation in East Asian facial expression is more common. Little gender variation is discovered in Caucasian facial expressions. Given that there are fewer gender stereotypes in Western society, this finding further verifies that gender stereotypes can remould the inborn universal facial behavior.

The finding in the thesis can be applied to facial recognition algorithm to enhance model performance. For example, model can be trained with information that some specific AUs need to be paid more "attention". In addition, there are still some limits due to the specifications of data and models,. The data of AU detection in the thesis is collected by the Openface. However, the training sets of neutral networks model in the Openface is consisted by a majority of Caucasian observations. Hence, it may not be rejected that the Openface can detect East Asian AU occurrence with error. There is another concern that some AUs are highly correlated. The high correlation terms may challenge the internal validation of the logit regression model and further research is required.

6.2 Future Work

- This thesis only used two datasets, which are CK+ and TFEID. In the gender variation analysis, only the peak emotion image is used and most non-peak emotion images are filtered out. Thus, the total images utilized in this part is not desirable. For example, there is only seven sad expression images in Caucasian men. Therefore, more facial expression images are demanded to achieve a more reliable conclusion.

- From the thesis, a statistical difference between Asian and Caucasian facial expressions has been found. This research majorly adopts Openface training modules in detecting the occurrence of AU. However, it is still possible that Openface mismeasures AU's appearance among Asian groups. Given the fact that Openface is trained from Caucasian-dominated training datasets, the prediction error among the Asian group may lead to incorrect AU detection result. Therefore, further research may need first to train a AU detector using Asian facial datasets.

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APPENDICES

Appendix A

Facial Action Coding System

AU	Description	Facial Muscles	AU	Description	Facial Muscles
1	Inner Brow Raiser		18	Lip Puckerer	
2	Outer Brow Raiser		20	Lip Stretcher	
4	Brow Lowerer		22	Lip Funneler	
5	Upper-Lid Raiser		23	Lip-Tightener	
6	Cheek Raiser		24	Lip Pressor	
7	Lid Tightener		25	Lips Part	
9	Nose Wrinkle		26	Jaw Drop	
10	Upper-Lip Raiser		27	Mouth Stretch	
11	Nasolabial Deepener		28	Lip Suck	
12	Lip-Corner Puller		41	Lid Droop	
13	Cheeks Puffer		42	Slit	
14	Dimpler		43	Eyes Closed	
15	Lip-Corner Depressor		44	Squint	
16	Lower-Lip Depressor		45	Blink	
17	Chin Raiser		46	Wink	

Figure A.1: Adult's Codes in Facial Action Coding System [1]

Appendix B

MATLAB code for action unit intensity calculation

```
%%%%%%%%%%%% Functions %%%%%%%%%%%%

%%% Angle of two vectors %%%
function k = angle(x_neutral,y_neutral, x_emotion,y_emotion, a
   ,b)

    pt1 = [x_emotion(a) y_emotion(a)];
    pt2 = [x_emotion(b) y_emotion(b)];
    vector1 = pt2-pt1; %vector1: line that goes through
       landmark pts a & b in emotional expression
    pt3 = [x_neutral(a) y_neutral(a)];
    pt4 = [x_neutral(b) y_neutral(b)];
    vector2 = pt4-pt3; %vector2: line that goes through
       landmark pts a & b in neutral expression
    k = max(min(dot(vector1,vector2)/(norm(vector1)*norm(
       vector2)),1),-1);
    k = real(acosd(k)); %angle of two vectors

end

%%% Average displacement of landmarks between neutral and
   emotional expressions %%%
```

```
function mag = displacement(x_neutral,y_neutral, x_emotion,
   y_emotion, k)

    d = 0;
    for i = k
        d = d + ((x_neutral(i)-x_emotion(i))^2+(y_neutral(i)-
           y_emotion(i))^2)^0.5; %Sum of displacement of
           landmarks with index k (k is a array of numbers)
    end

    l = length(k);
    mag = d/l;

end

%%% Distance between two landmarks %%%
function mag = d_twopts(x_neutral,y_neutral, a,b)

    pt1 = [x_neutral(a),y_neutral(a)];
    pt2 = [x_neutral(b),y_neutral(b)];
    vector = pt2-pt1;
    mag = norm(vector);

end

%%%%%%%%%%%% AU intensity %%%%%%%%%%%%

%%% AU1 inner brow raiser %%%
inner_brow = displacement(x_neutral,y_neutral, x_emotion,
   y_emotion, [22,23]);
eyebrow = (d_twopts(x_neutral,y_neutral,18 ,22)+ d_twopts(
   x_neutral,y_neutral,23 ,27))/2;
inner_brow = inner_brow/eyebrow; %normalized

%%% AU2 outter brow raiser %%%
outter_brow_raiser = (angle(x_neutral,y_neutral, x_emotion,
   y_emotion, 18,19) ...
    +angle(x_neutral,y_neutral, x_emotion,y_emotion, 26,27))
```

```
    /2;

%%% AU4 Brow lowerer %%%%
eyebrow = (d_twopts(x_neutral,y_neutral,18 ,22)+ d_twopts(
   x_neutral,y_neutral,23 ,27))/2;

brow_lower = (displacement(x_neutral,y_neutral, x_emotion,
   y_emotion, 18) + ...
    displacement(x_neutral,y_neutral, x_emotion, y_emotion,
       19) + ...
    displacement(x_neutral,y_neutral, x_emotion, y_emotion,
       20)+ ...
    displacement(x_neutral,y_neutral, x_emotion, y_emotion,
       25) + ...
    displacement(x_neutral,y_neutral, x_emotion, y_emotion,
       26) + ...
    displacement(x_neutral,y_neutral, x_emotion, y_emotion,
       27))/eyebrow;


%%% AU 5 upper lid raiser %%%
emotion_lid = d_twopts(x_emotion, y_emotion, 38,42)+d_twopts(
   x_emotion, y_emotion, 39,41)+ ...
    d_twopts(x_emotion, y_emotion, 44,48) + d_twopts(x_emotion
       , y_emotion, 45,47);

neutral_lid = d_twopts(x_neutral, y_neutral, 38,42)+d_twopts(
   x_neutral, y_neutral, 39,41)+ ...
    d_twopts(x_neutral, y_neutral, 44,48) + d_twopts(x_neutral
       , y_neutral, 45,47);

upper_lid_raiser = emotion_lid/neutral_lid - 1;

%%% AU 6 Cheek raiser  %%%
emotion_lid = d_twopts(x_emotion, y_emotion, 38,42)+d_twopts(
   x_emotion, y_emotion, 39,41)+ ...
    d_twopts(x_emotion, y_emotion, 44,48) + d_twopts(x_emotion
       , y_emotion, 45,47);
```

```
neutral_lid = d_twopts(x_neutral, y_neutral, 38,42)+d_twopts(
   x_neutral, y_neutral, 39,41)+ ...
    d_twopts(x_neutral, y_neutral, 44,48) + d_twopts(x_neutral
       , y_neutral, 45,47);

cheek_raiser = abs(emotion_lid/neutral_lid - 1);

%%%AU 7 Lid Tightener %%%%
emotion_lid = d_twopts(x_emotion, y_emotion, 38,42)+d_twopts(
   x_emotion, y_emotion, 39,41)+ ...
    d_twopts(x_emotion, y_emotion, 44,48) + d_twopts(x_emotion
       , y_emotion, 45,47);

neutral_lid = d_twopts(x_neutral, y_neutral, 38,42)+d_twopts(
   x_neutral, y_neutral, 39,41)+ ...
    d_twopts(x_neutral, y_neutral, 44,48) + d_twopts(x_neutral
       , y_neutral, 45,47);
lid_tightner = abs(emotion_lid/neutral_lid - 1);


%%% AU 10 Upper lip raiser %%%
upper_lip_raiser =  abs(d_twopts(x_emotion,y_emotion,34,52)/
   d_twopts(x_neutral,y_neutral,34,52)-1);

%%%AU 11 Nasolabial deepener %%%%
Nasolabial = d_twopts(x_emotion,y_emotion,32,36)/d_twopts(
   x_neutral,y_neutral,32,36)-1;

%%% AU12 Lip corner puller %%%
lip_corner_puller = abs(d_twopts(x_emotion,y_emotion,49,55)/
   d_twopts(x_neutral,y_neutral,49,55)-1);

%%% AU 15 lip corner depressor %%%
lip_corner_depressor = abs(d_twopts(x_emotion,y_emotion,49,55)
   /d_twopts(x_neutral,y_neutral,49,55)-1);

%%% AU 25 lip apart %%%
```

```
lip_apart = d_twopts(x_emotion, y_emotion, 63,67)/d_twopts(
   x_neutral, y_neutral, 63,67)-1;

%%% AU 26 Jaw drop %%%
jaw_drop = d_twopts(x_emotion, y_emotion, 28,9)/d_twopts(
   x_neutral, y_neutral, 28,9)-1;
```

Appendix C

Sixty Eight Facial Landmarks Annotation

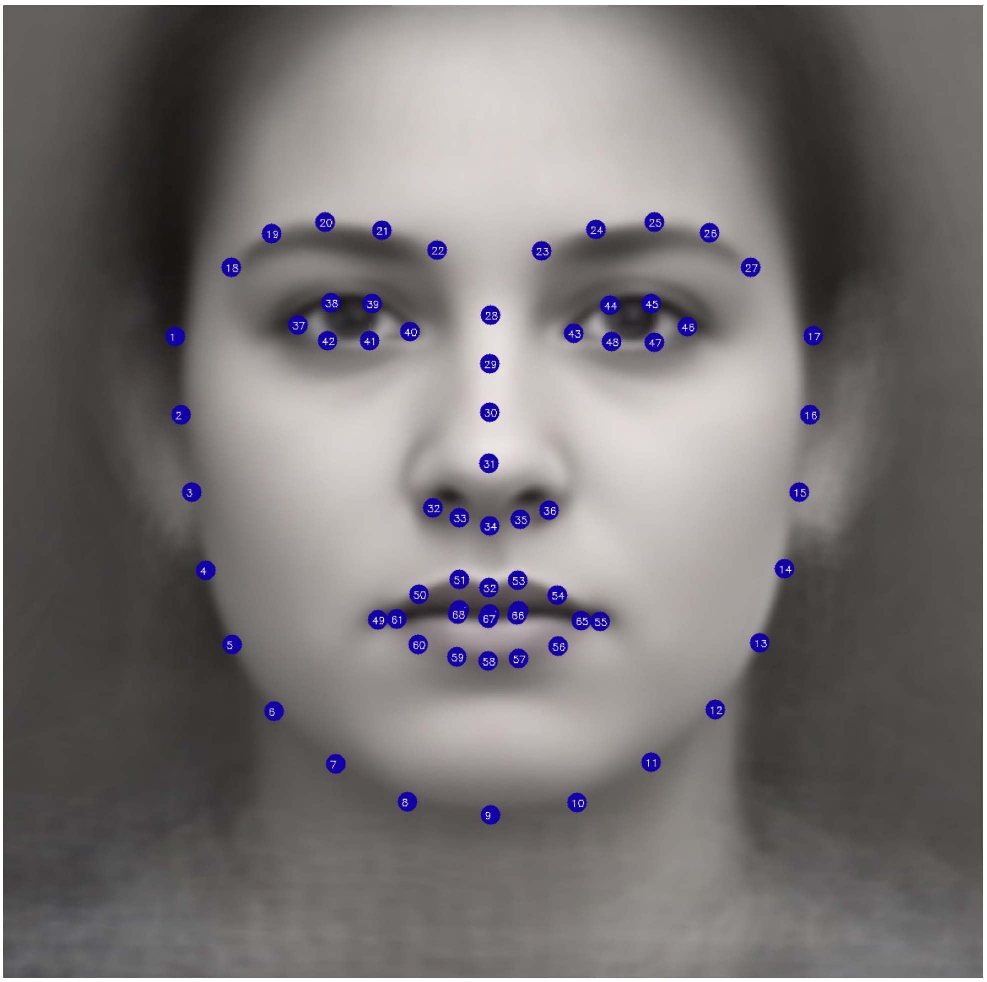

Figure C.1: 68 facial landmarks annotation

Appendix D

Logit Regression Result with Emotion as Dependent Variable

Table D.1: Logit Regression Result of ....

	Dependent variable:	
	Surprise vs. Happy	
	East Asian	White Caucasian
Action Unit		
AU01	-0.636	0.481^{*}
	(0.624)	(0.262)
AU02	-0.249	-1.433^{***}
	(0.637)	(0.246)
AU04	0.256	-0.693^{**}
	(0.653)	(0.303)
AU05	-1.475^{***}	-0.153
	(0.552)	(0.208)
AU06	19.166	1.540^{***}

	(1,128.541)	(0.365)
AU07	1.002	0.470**
	(1.588)	(0.219)
AU09	−1.246	0.533**
	(4,839.518)	(0.210)
AU10	0.178	1.977***
	(0.864)	(0.471)
AU12	−0.968	1.914***
	(1.347)	(0.274)
AU14	1.685	1.777***
	(1.461)	(0.209)
AU15	−0.078	−1.051***
	(0.569)	(0.200)
AU17	0.028	−0.690**
	(0.888)	(0.276)
AU20	0.817	0.601***
	(0.527)	(0.214)
AU23	−0.363	−0.369*
	(0.551)	(0.211)
AU25	−0.485	−1.633***
	(0.571)	(0.298)
AU26	−0.278	−0.711***
	(0.599)	(0.230)
AU28	−17.310	1.255***
	(4,340.399)	(0.451)

AU45	−0.448	0.806***
	(0.703)	(0.218)
Constant	0.655	−1.100***
	(0.934)	(0.352)
Observations	235	2,054
Log Likelihood	−69.660	−396.391
Akaike Inf. Crit.	177.321	830.783
Note:		*p<0.1; **p<0.05; ***p<0.01