HUMAN GAIT ANALYSIS OF DIFFERENT EMOTIONS IN REAL-TIME VIDEO VIEWING

リアルタイムの映像視聴における異なる感情についての人間の歩容解析

A DOCTORAL DISSERTATION PRESENTED

BY

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Abstract

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Emotion recognition and analysis are useful in many circumstances. It can be used to avoid altercations and crimes, improve customer experience, and improve student concentration in online learning. Traditional methods for detecting and analyzing emotions are developed using facial features, which require close-up facial information that cannot be obtained from standard security cameras. Postures and gait features can be observed noninvasively from afar unlike other biometrics such as facial features, iris, and eye movements. The relationship between human emotions with their gaits and postures were analyzed in this study. Experiments were conducted with two datasets consisting of 49 participants and 23 participants walking in a circular pattern, either clockwise or counter-clockwise, in the recording area while watching emotion-inducing videos on Microsoft HoloLens 2 smart glasses. Their postures and gait characteristics were recorded using OptiTrack motion capturing system. Angles between body parts and the walking straightness of participants in three different emotions including happy, sad, and neither were calculated as gait features. The differences in body parts movements of participants while they are walking and watching emotional videos were examined. Statistical results show that the arm swings are significantly different between happy emotion and sad emotion. Also, while subjects are feeling happy, their outside arm swings are statistically larger than their inside arm swings. The findings of this study reveal that human emotions can be effectively recognized using arm movements with taking arm side and walking straightness information into consideration as well. To the best of my knowledge, this is the first study that uses emotional videos to induce emotions of the participants while they are walking and watching the videos on smart glasses at the same time. These findings have the potential to advance the field of emotion recognition and analysis using human gaits and postures.

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Chapter 1

Introduction

Emotion recognition and analysis have gained popularity in recent years due to its usefulness in a variety of applications such as improving the quality of human-robot interaction, evaluating customer satisfaction, detecting suspicious behaviors for crime prevention, assessing student engagement during online classes, and so forth. It can be used to avoid violence among groups of people by recognizing when one or more people in a heated debate become uncomfortable. Appropriate personnel could intervene, and remove the members from the group. Emotional recognition and analysis can also be utilized in marketing, such as determining whether an advertisement elicits a good response from people passing by. Many of these uses can improve the quality of life of humans.

Because of the importance of human emotion analysis research, there is a dedicated research area called *Affective Computing* [33] that aims to train computers to comprehend and generate human-like affects that may be applied to a variety of applications. Many affective computing applications have been proposed in recent years. Several works are highly helpful in today's pandemic crisis, particularly for educational purposes, as most students are unable to attend on-site sessions. Students who would like to practice their programming abilities at home cannot receive face-to-face supervision from instructors; hence, they cannot develop their skills as effectively as they would in a normal situation. The online exercise application can estimate how students perform in each assignment by incorporating affective computing technology. If the students do not perform well in any assignment, they can perhaps feel drained or bored. The program can advise the students to focus on their weak points in that assignment, and can interact with the students using animated agents to make them feel positive so they can continue studying effectively and happily [42].

Unfortunately, predicting a subject's emotion using human observers is an expensive, time-consuming operation that is not accurate enough to be used in practice. Many methods for automatic emotion prediction have been developed; however, the majority of publicly available methods now employ facial expressions as input for analysis and prediction. Facial features operate well in some scenarios but have limitations, such as becoming more difficult to obtain in noisy environments and by conventional security cameras. Furthermore, some people do not show intense emotions on their faces. Because of these restrictions, emotional detection approaches based on facial features are only useful in certain scenarios, particularly when the individuals' faces can be clearly captured, such as when they are facing forward near the camera. If face photos cannot be clearly recorded, other features are required to make emotion prediction and analysis applications more accurate and suitable for real-world deployment.

Human gaits and postures are the manner in which the human body moves and poses when walking or performing other tasks. Gaits and postures can be monitored from afar without the need for high-resolution photos or videos. The collection of gaits and posture characteristics does not interfere with the individuals' daily lives. These data can even be gathered without the subjects' knowledge. Gaits and postures recognition have been employed effectively in a variety of applications, including human identification [18, 26], human re-identification [27], human age estimation, and gender recognition [12, 21]. Hence, human gait and posture are appropriate features to detect human emotions as shown in several previous studies [3, 6, 14, 17, 24, 25, 30, 34, 35, 44, 47].

The goal of this study is to examine the changes in human gaits and postures when humans are feeling different emotions. Experiments were conducted to see how different body parts move in different emotions and if these movements can be utilized to determine subjects' emotions. The participants for the experiments are undergraduate university students, both male and female. While watching emotion-inducing videos, participants were asked to walk in their natural manners on a non-straight walking path.

Traditional techniques of showing videos to individuals before walking have the possibility that the induced emotions are not consistent and do not last until the end of the walk. Furthermore, if the videos are shown on a regular screen while a subject is walking in a non-straight pattern, the subject must bend or turn his or her head to watch the videos on the screen. With my proposed method, the individual can see the videos immediately on HoloLens 2, allowing him or her to walk naturally while also watching the video. This method can ensure that induced emotion is more consistent and lasts until the end of the walk. In this study, one-way and multi-factor analysis of variance (ANOVA), as well as linear regression analysis were used to analyze all gait data.

Experiments and analyses were performed to prove two hypotheses in this study. The first hypothesis is that body part movements while walking differ in different emotions, so walking postures can reveal subjects' emotions. The second hypothesis is that body movements of the left and right sides while walking on a non-straight path are not symmetric, and one body side can reveal subjects' emotions better than the other. This study is different from other conventional studies since it focuses on human gaits analysis while the subjects walk in a non-straight walking path.

In conclusion, the results of statistical analyses show that human gaits and postures vary according to emotions, particularly left arm swing movements.

This dissertation is organized as follows. The overview of this study is shown in Chapter 1. Then, other works which are related with this study are mentioned in Chapter 2. Data collection that was used in this study is explained in Chapter 3. This chapter includes data collection method, equipment used in data collection, recording environment setup, materials for emotion induction and information of collected dataset. Chapter 4 shows the method that was used to preprocess the collected data before using. Gait features extraction methods are listed in Chapter 5. Statistical analyses of gait features for this dataset are described in Chapter 6. Additionally, another data collection was performed so the second dataset collection, preprocessing as well as features extraction, and statistical analyses of this dataset are explained in Chapter 7, Chapter 8, and Chapter 9 respectively. Discussion and explanation of analyses results for both datasets are described in Chapter 10. Lastly, the summary and conclusion of the entire study are shown in Chapter 11.

Chapter 2

Related Works

Because of the field's popularity and usefulness, several studies on emotion recognition have been proposed in recent years. The majority of these works, however, are based on facial expression. These studies produce accurate results for some applications but have limitations in other real-world applications, as discussed in the previous chapter. Fewer studies have been conducted on emotion recognition based on gaits and postures.

A survey study by Xu et al. [46] investigated numerous studies on gait analysis. They found that gait analysis can be used not only for subject identification but also for subject current emotion prediction. They discovered that people walking in different emotions exhibit different characteristics. This data can be used to perform automatic emotion recognition. When compared to traditional biometrics such as facial features, speech features, physiological features, and so forth, using gaits has several advantages. For instance, gaits can be observed from afar without the subject's awareness. It is difficult to imitate gaits. Gaits can be obtained without cooperation of the subject. Because of these advantages, gaits are effective form of expressions which can be used for automatic emotion recognition. Many different devices can be used to record gaits.

For example, a force plate can be used to record velocity and pressure data [14]. The infrared light barrier system is also effective for recording velocity data

[14, 23]. Motion capturing system such as Vicon can accurately capture coordinate data using markers attached to the body [3, 8, 9, 17, 29, 35, 44]. Microsoft Kinect is another useful tool for capturing human skeletons by combining depth and color images to predict the position of body joints [18, 21, 24, 25, 26, 27, 41]. The accelerometer sensor on wearable devices like smartphones or smart watches can also record movement data for gait analysis [6, 34, 47]. There are several preprocessing steps that can be used after collecting gait data. For instance, low pass Butterworth filter [8, 15, 16], sliding window Gaussian filtering [24, 25]. Data transformation from time domain to others including Discrete Fourier Transform [24, 25, 41] and Discrete Wavelet Transform are also widely used [2, 13, 31]. Gait features are categorized into Spatio-temporal Features such as stride length, velocity, step width, step length and Kinematic Features such as coordinates data, joint angles, angular range of motion etc. Dimension reductions are also used e.g., Principal Component Analysis [7, 32, 36, 40, 45]. Finally, emotion recognition phase can be performed using many popular techniques, e.g., Multilayer Perceptrons [14], Naive Bayes [17, 24, 25], Nearest Neighbors [1, 17], Support Vector Machine [6, 17, 24, 25, 47], Decision Tree [1, 6, 47]. Finally, there are some interesting findings from several studies they surveyed. For happiness, the subject steps faster [30], strides are longer [10], arm movement is larger [10], and joint angle amplitude increases [35]. For sadness, the arm swing decreases [30], torso shape and limb shape contract [9], and joint angles amplitudes reduce [35].

There are many gait analysis studies proposed in recent decades. Several applications can be achieved by analyzing human gaits. The following are some examples; human identification or re-identification [18, 26, 27], gender prediction [12, 21], emotion prediction [14, 46], mental illness prediction [23, 29]. There are several aforementioned methods to collect gait data such as using force plate, light barrier, motion capturing system, video camera, accelerometer, and so forth. This study focuses only the methods that extract 3-dimensional coordinates, binary silhouette, and body parts angles as gait features since these gait features are sensitive to walking pattern. Most studies proposed nowadays used straight walking path in their experiments to achieve high quality gait data [3, 6, 14, 15, 16, 23, 24, 25, 29, 35, 36, 41, 44]. However, fewer studies used free-style walking path where the subjects can choose any walking pattern they wanted instead of straight walking [18, 21, 26, 27]. By developing methods for free-style walking data, opportunities for the proposed methods to be implemented in real-world scenarios, where humans are walking without awareness of being observed in public spaces, are increased because obtaining adequate straight walking data in a noisy environment is more difficult than free-style walking data.

Since Microsoft HoloLens 2 smart glasses were used to show the videos to each participant while they were walking, another issue to consider is whether or not watching content on smart glasses will interfere with gaits. Slips and trips pose a risk of negative effects. There are some studies done on this topic. Kim et al. [20] investigated gait performance while walking with a head-worn display. They used 12 participants in their experiments to see if the subjects could walk effectively in a variety of conditions while wearing a head-worn display or not. They measured the minimum foot clearance, the required coefficient of friction, the location of the foot placement around the obstacle, the walking speed, and the obstacle crossing speed. They discovered that using a head-worn display has no effect on level walking performance when compared to a paper list and baseline walking using nothing. When subjects used the head-worn display to perform obstacle crossing tasks, they choose a more conservative and cautious strategy, and their obstacle crossing speed decreases by 3% compared to the baseline. However, when using a head-worn display, the location of foot placement around the obstacle is unaffected.

Negative effects on human gaits when subjects use head-worn displays such as smart glasses while walking were investigated [38, 39]. In their experiments, 20 participants (10 men and 10 women) walked on a treadmill at their preferred walking speed in four different conditions. They asked the subjects to do one single-task walk and three dual-task walks while using different equipment to display information to them while walking. Participants in dual-task walkings conducted attention-demanding tasks on various display types. Stroop test, categorizing, and arithmetic are examples of attention-demanding tasks. Paper-based systems, smartphones, and smart glasses were used as displays in their experiments. The subjects use the head-down posture for paper-based displays and smartphones, but the head-up posture for single task walking and smart glasses display. Vicon motion capture system with 7 cameras was used for motion capture. They discovered that using smart glasses to perform tasks while walking has a greater impact on gait performance, such as stability, than using other types of display. They also discovered that smart glasses can interfere with the control of gait variables. However, when using a smartphone and a paper-based system, participants are more unstable than when using smart glasses.

This study was designed to investigate the difference of human gaits in different emotions, arm swing is also an important movement of gaits which is considered in this study. It is possible that the movement of left arm and right arm can be asymmetric. Hence, studies related with asymmetric arm movement are explored. Kuhtz-Buschbeck and coworkers [22] performed the experiments to check whether the arm swing of left arm and right arm are symmetric when the subjects are walking on a treadmill. Dominant and non-dominant sides of body are possible causes if the arm swing is not symmetric. Three walking conditions were used in their experiments including forward walking, running, and backward walking. Sixteen subjects consisted of 8 men and 8 women participated in their study. Numbers of left-handed and right-handed are balanced. They found that arm swing is frequently asymmetric within the same subject i.e., nearly half of trials (47 of 96 trials) have significant side differences. There are 22 trials that have more arm swing in dominant hand side and 25 trials in non-dominant hand side. Majority of subjects have consistent asymmetric arm swing (10 of 16 subjects). Therefore, asymmetry in arm swing is a normal phenomenon regardless of dominant hand side.

Moreover, there is a recent study that investigated the asymmetry issue of arm swings when subjects are walking. Killeen et al. [19] performed tests on arm swing symmetry of 334 subjects including 176 male and 158 female subjects. The average age of subjects is 68.6 years with 5.9 years standard deviation. The subjects were asked to walk along 20 meters walkway and walk back for one minute. The walking postures when the subjects turning back were removed and only straight walking parts were used in their study. There were two walking velocity in this experiment including normal walking and fast walking. Both velocity were not specified and subjects could decided their own speed. Three tasks were performed by each subject. First task is normal walking, second task is fast walking, and third task is fast walking while doing serial subtraction which is a cognitive task during walking. In the third task, which is a dual-task walking, subjects were asked to not prioritize any task over another i.e., perform walking and serial subtraction equally. Their results reveal that the arm swing of left arm is significantly larger in all conditions. Subjects who have larger left arm swing also have more significantly different arm swing between single-task and dual-task walking. However, for the subjects who have larger right arm swing, they do not have significantly different arm swing between different tasks. Interestingly, asymmetry of arm swings is lower when the subjects are performing dual-task walking compared with single-task walking. About the dominant hand effect on arm swing, this study found that subject's dominant hand does not affect arm swing's asymmetry. Also, female subjects have lower asymmetric arm swings compared to male subjects. From this study, it is normal that left arm swings are larger than right arm swings when the subjects walk regardless of whether they are doing cognitive tasks or not.

According to these related studies, Microsoft HoloLens 2 can be used for displaying emotional videos to the participants while they are walking in the recording area, despite the possibilities that some negative effects, such as walking instability, can occur when using smart glasses while walking. This issue can be solved by asking the participants to take one rehearsal walk in the walking area without wearing HoloLens 2 to make them familiar with the walking area and one rehearsal walk with wearing HoloLens 2 that showed nothing to make them familiar with walking while wearing smart glasses at the same time.

About the walking pattern, straight walking should result in cleaner gait data, but it has more constraints when being implemented in real-world circumstances. However, walking freely without any path guidance will be tough for the subjects because they must concentrate on the video displayed on HoloLens 2 while walking. Hence, they will be unable to focus on the videos' content because they must decide the walking path at the same time. As a result, experiments were done with the lax circular walking path. Both straight and non-straight walking data can be obtained in one walking trial by walking circularly in a clockwise or counter-clockwise direction without marking the path line on the floor.

Chapter 3

Data Collection

Data collection is the first process that was done for this study. Since there is no publicly available dataset that meets the requirements for studying the effects of non-straight walking behaviors according to different emotions, a novel data collection method that no one used before was applied to perform data collection.

Most previous researches in the fields of emotional recognition and analysis requested participants to walk in a straight line after watching emotional movies or to walk in a straight line while thinking about personal experiences. These settings have a number of flaws. When participants are instructed to walk after watching emotional videos, it is likely that some will not feel the same emotions till the end of the walk, or that some will not feel any emotion at all after watching the videos. As a result, the relationship between gaits and emotions may be inaccurate. In cases where participants were asked to feel certain ways based on personal experiences, it is possible that some participants will be unable to recall their feelings well enough to reflect on their body movements. These causes can result in incorrect information.

To avoid issues that lead to faulty information and an inaccurate relationship between gaits and emotions, the experiments are designed to make participants constantly incited with emotion-induced videos while walking. Microsoft

HoloLens 2, which is the latest smart glasses technology, was used to show videos to subjects while they were walking. To the best of my knowledge, this type of emotion induction method has never been used before. Using HoloLens 2 to display videos makes subjects to be able to see the room environment and the videos at the same time. Because emotional videos were shown to participants while they walk, the results are more similar to real-life situations in which a subject experiences some events and feels some emotions as a result of those events. In other words, this study tried to simulate the participants' real-time emotion by displaying them emotion-induced videos while they walked. Furthermore, the intensity of induced emotions should be more consistent than the conventional method, which had individuals watch emotional videos before walking. In reality, emotions of humans can be changed quickly in real-time according to the stimuli such as situations or events. However, inducing several emotions in one walking trial will be difficult to be done effectively. Because each subject has different perceptions of emotions e.g., not all subjects will feel sad when watching sad videos and not all subjects will feel happy when watching happy videos, it is possible that the perceived emotion of different subjects will be different from the annotated emotion of emotion-inducing video even if the video is identical for all subjects. To cope with this challenge, if a video contains only one annotated emotion, asking the subjects about their perceived emotion and using the *Reported Emotion* for labeling a walking trial should be better than labeling a walking trial using the annotated emotion of the video i.e., *Expected Emotion* from the stimulus. However, because this study was designed to use HoloLens 2 for showing videos to the subjects while walking, asking all subjects to report their perceived emotions can be done after finished walking only. If a video contains several annotated emotions, subjects need to report their perceived emotions several times which is very difficult to do during walking. Therefore, the scope of this study is limited to inducing only one emotion for an entire walking trial.

3.1 Equipment for Data Collection

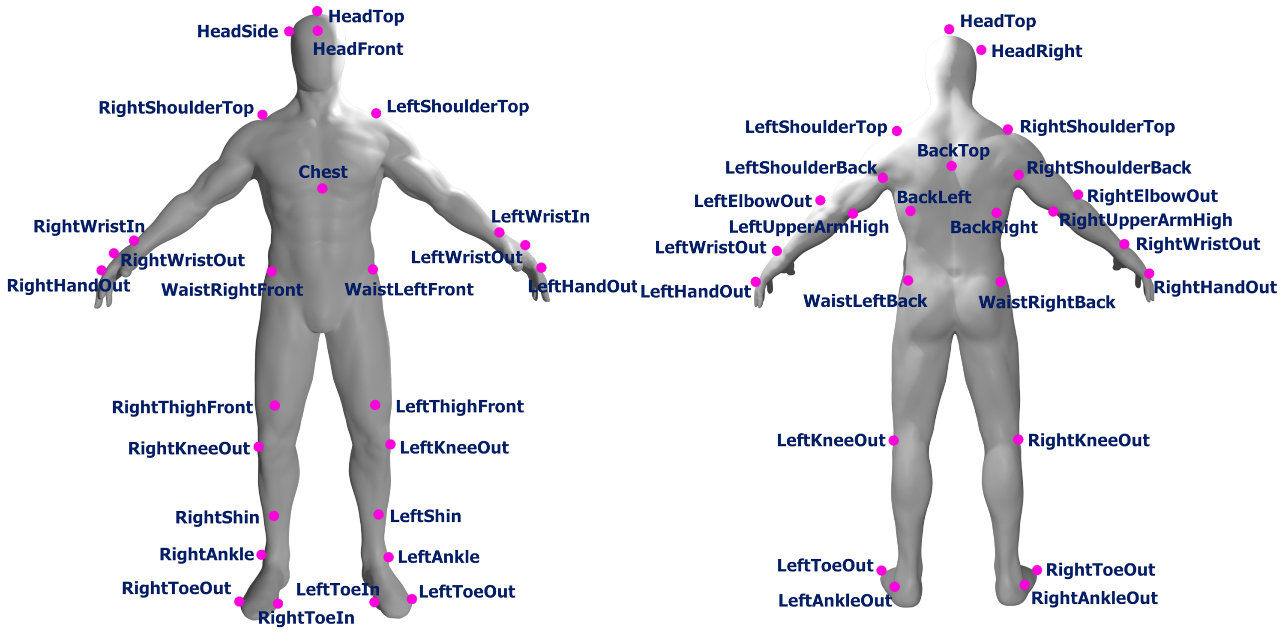

Figure 3.1: Position of Front and Back Markers (Original Human Figure Source: dog012 on Sketchfab[2])

There are two types of motion capturing technology currently available: markerless and marker-based systems. In markerless system, image processing technology uses depth data from an infrared camera and RGB images from a color camera to calculate the coordinates of body parts. Because there is

[2] https://sketchfab.com/3d-models/man-5ae6bd9271ac4ee4905b96e5458f435d

no need to attach any equipment to the subject's body, markerless devices are more convenient to employ in real-life situations. For marker-based systems, multiple markers must be attached to the subject's body in the appropriate positions, such as the head, hand, elbow, etc. The marker-based device is more difficult to set up since it requires many cameras to record the infrared reflections from the markers attached to the subject's body in order to reconstruct markers coordinates in three dimensional space. However, body tracking accuracy of markerless device is lower than marker-based type since markerless system predicts the position of each body parts while marker-based type uses the actual position obtained from several cameras.

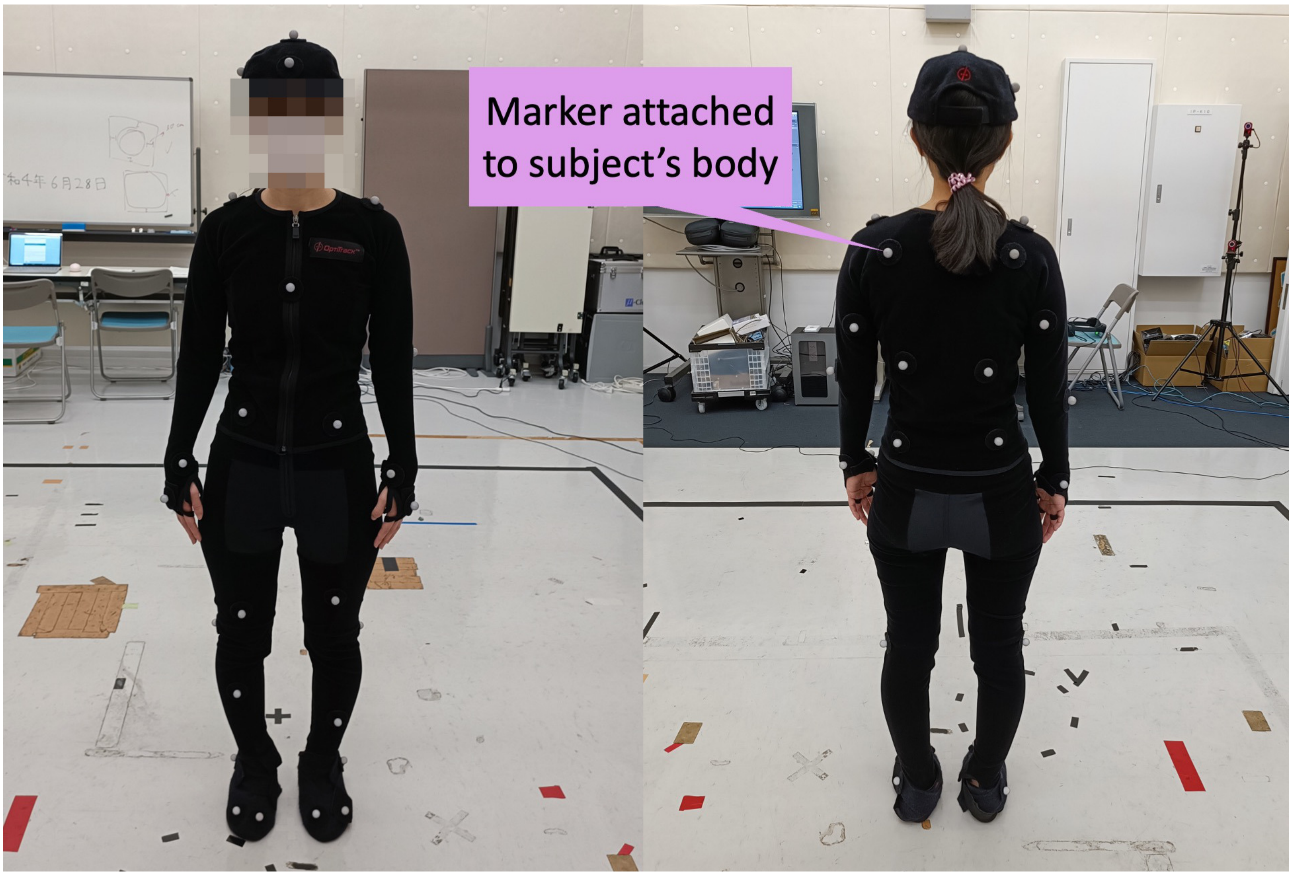

Figure 3.2: Attached Markers on Subject's Body

In this research, gait data were collected using OptiTrack, a well-known marker-based motion capturing system. The standard 37-marker, which is the baseline marker set for human skeleton tracking, was used. With the baseline marker set configuration, 37 markers were attached to each subject's body. The names of the markers are listed in Table 3.1, and their positions are visualized in Figure 3.1. An example of the markers attachment on OptiTrack motion capture suit is shown in Figure 3.2. In this study, fourteen OptiTrack Flex 3 cameras were used for recording gait data. Two cameras were installed on each camera stand as shown in Figure 3.3.

Figure 3.3: Two OptiTrack Flex 3 Cameras were Installed on One Camera Stand at Different Height Levels

3.2 Recording Environment

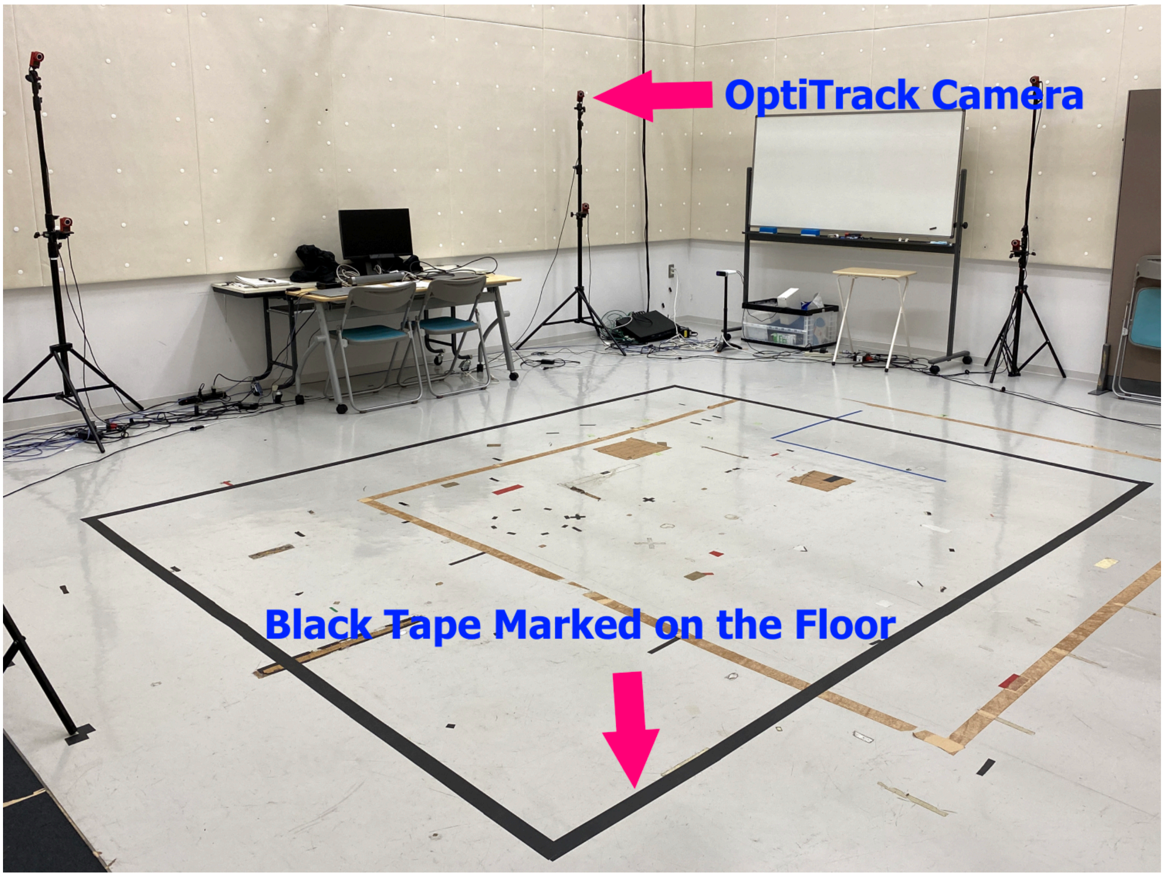

Figure 3.4: Rectangle Walking Area Marked with Black Tape on the Floor

The black tape was used to mark a rectangle on the floor as the walking area that the OptiTrack motion tracking system can capture, as shown in Figure 3.4. On seven camera stands, fourteen OptiTrack Flex 3 motion capture cameras were installed. That is, two cameras at different heights on each stand, as shown in Figure 3.3. In Figure 3.5, seven camera stands were placed around the walking area. And the walking area is 2.9 meters by 3.64 meters in size.

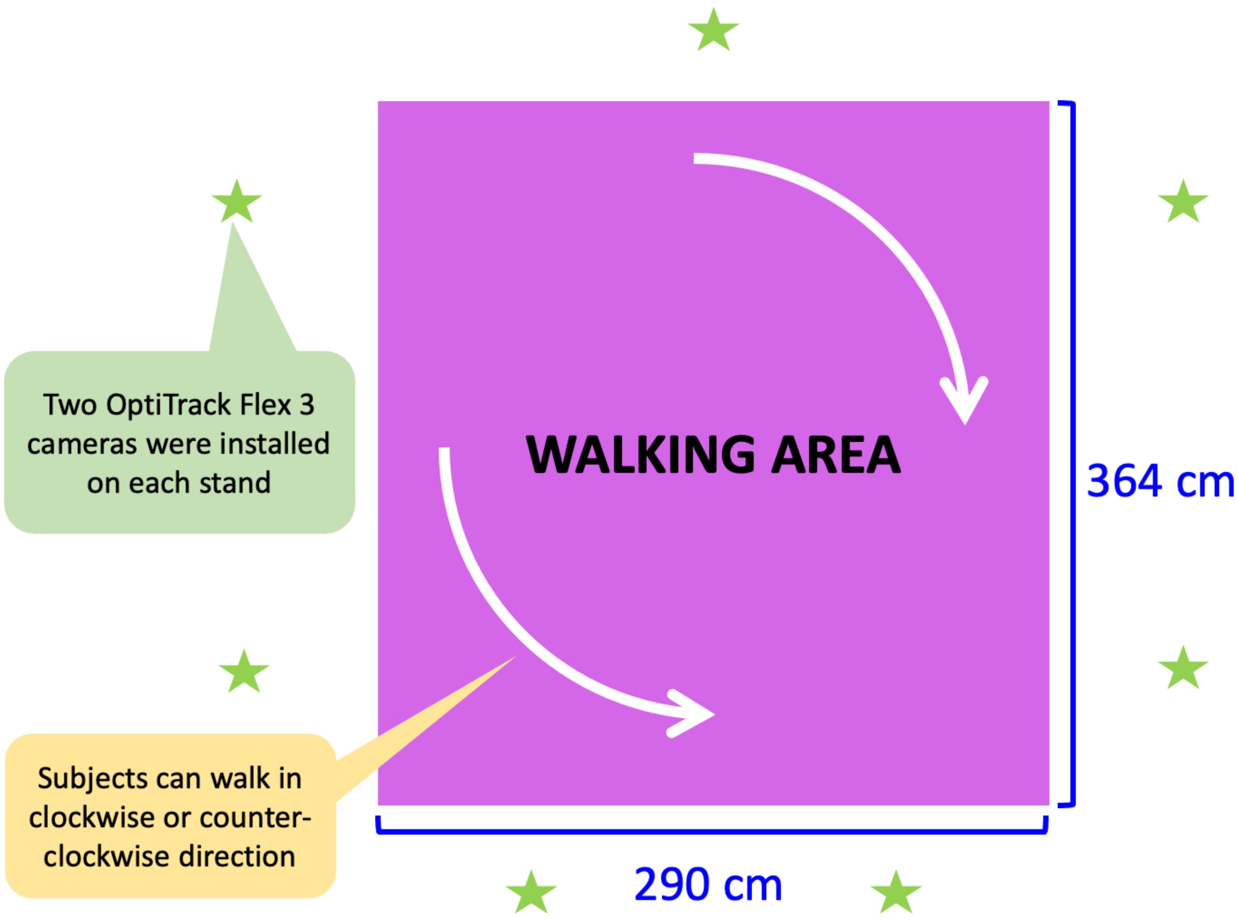

Figure 3.5: Size of Walking Area and Position of Recording Equipment (OptiTrack Flex 3)

3.3 Materials for Data Collection

Three videos were selected as stimuli for emotion induction. HoloLens 2 were used for showing videos to the subjects while they walked in the recording area.

- **Neutral Video:**

  The nature landscape video from YouTube named *Spectacular drone shots of Iowa corn fields* uploaded by the YouTube user named *The American Bazaar*[3]

[3]https://www.youtube.com/watch?v=4R9HpESkor8

- **Negative Video:**

  An emotional movie selected from *LIRIS-ACCEDE* database named *Parafundit* by *Riccardo Melato*

- **Positive Video:**

  An emotional movie selected from *LIRIS-ACCEDE* database named *Tears of steel* by *Ian Hubert* and *Ton Roosendaal*

The neutral video was chosen from nature landscape videos on YouTube that should not elicit any emotion. Positive video (inducing happy emotion) and negative video (inducing sad emotion) were chosen from the public annotated movie database[4] published by Baveye et al. [4]. Many creative commons movies and their emotional annotations are presented in this database. In this study, two movies from the Continuous LIRIS-ACCEDE collection were selected. This movie collection contains 30 movies and emotion annotations in Valence-Arousal ranking.

Most movies contain both positive and negative valence. To create an entire walking trial containing only one emotion, one movie with positive valence for the entire movie and one movie with negative valence for the entire movie were selected. The length of each video is also an issue need to be concerned, so all of the videos used in this study are less than than 15 minutes in length. The lengths of the neutral video, negative movie, and positive movie are 5:04, 13:10, and 12:14 minutes, respectively. The audio of both negative and positive videos includes music, sound effects, and conversations in English. When subjects

[4] https://liris-accede.ec-lyon.fr/

walk, they can hear the sound from the built-in speakers of HoloLens 2. The neutral video has no sound to ensure that it does not elicit any emotion.

3.4 Methods for Data Collection

Each participant was asked to answer the health questionnaire and sign the consent form in the beginning of the experiments. Questions in the health questionnaire are listed below.

1. Do you have any neurological or mental disorders?
2. Do you have a severe level of anxiety or depression?
3. Do you have hearing impairment that cannot be corrected?
4. Do you have any permanent disability or body injury that affects walking posture?
5. Do you currently feel sick now? (e.g., fever, headache, stomachache etc.)
6. If you have any problem with your health condition, please describe.

Each subject was instructed to walk in a circular pattern inside the marked rectangle space after he or she was confirmed to be healthy, i.e., that subject could walk, watch, and listen normally. Participants could choose whether they wanted to walk clockwise or counter-clockwise. Participants were free to change directions at any time during each walking trial. To establish a subject's natural walking style, Each subject was asked to walk in the recording area for

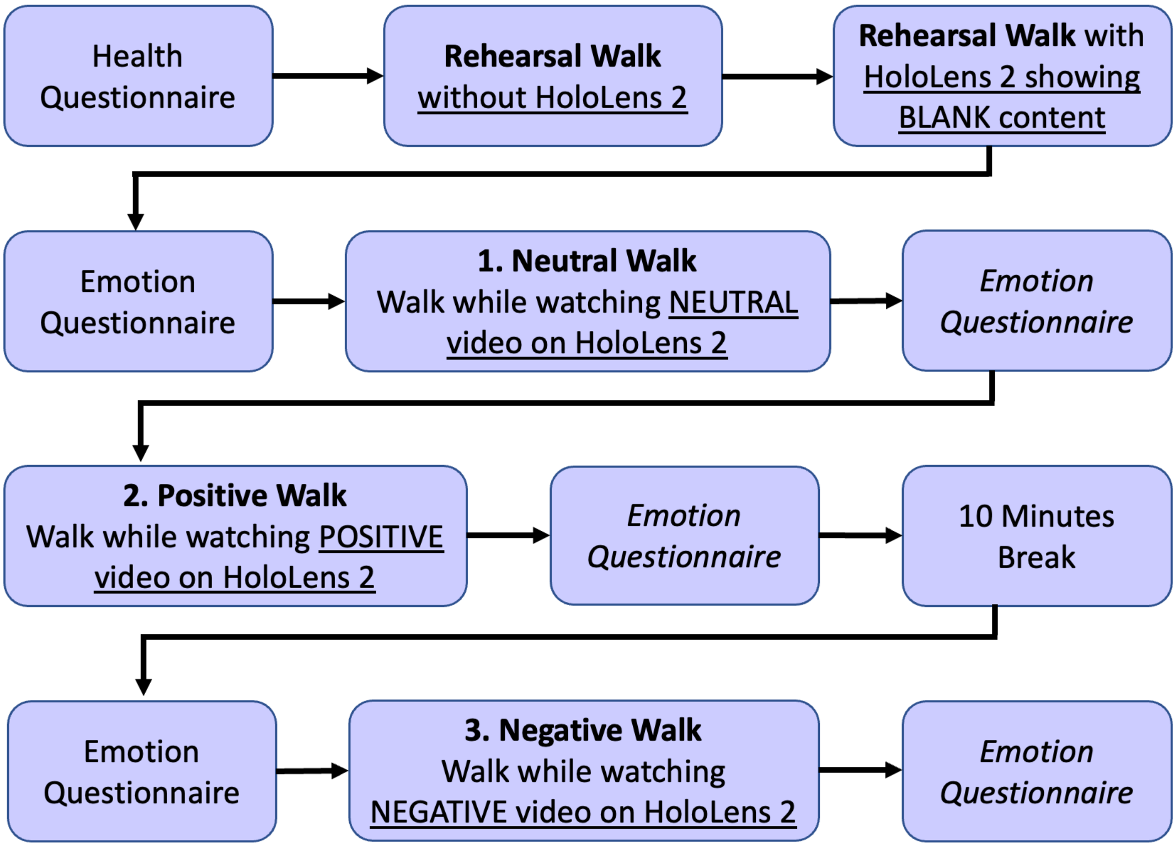

Figure 3.6: Data Collection Process

3 minutes without wearing the HoloLens 2. The objective of the first walking trial *(Rehearsal Walk)* is to familiarize the subject with the walking space.

The second *Rehearsal Walk* was conducted for each subject by walking for another 3 minutes while wearing HoloLens 2 that did not display any content to familiarize them with walking while wearing HoloLens 2. According to the findings of the following studies: [20, 38, 39], if participants have never used smart glasses while walking before, gait performance can be unstable. Before performing actual recording, subjects were instructed to take rehearsal walks with and without HoloLens 2.

Then, *Neutral Video* was shown on HoloLens 2 and each subject was re-

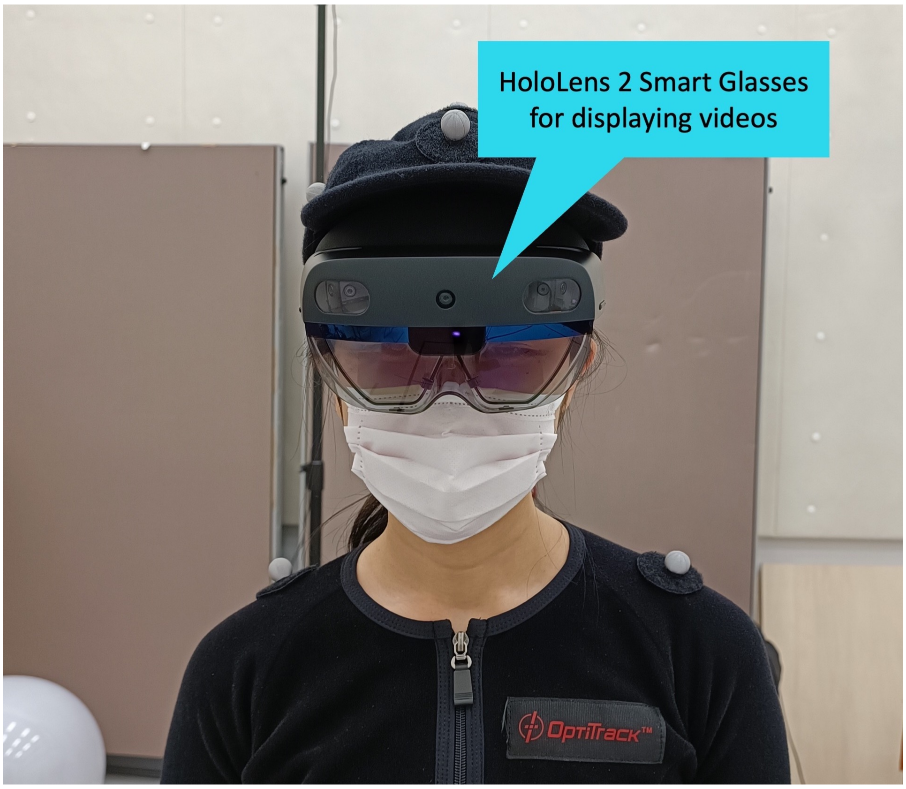

Figure 3.7: A Subject Wearing Microsoft HoloLens 2

quested to walk while watching the video to capture *Neutral Walk*. Each subject began to walk when the video started and stopped walking when the video ended. As described in Section 3.3, *Positive Walk* and *Negative Walk* were performed using *Positive Video* and *Negative Video* from the LIRIS-ACCEDE database. These videos were shown on HoloLens 2 while each subject was walking using the same procedure with *Neutral Walk*. As shown in Figure 3.7, HoloLens 2 has a transparent view so the subjects can see videos and room environment while walking unlike other virtual reality (VR) devices. Furthermore, after completing *Positive Walk*, subjects have to take a 10-minute break to allow their emotions to return to normal before beginning *Negative Walk*. For the next subject, the order of *Negative Walk* and *Positive Walk* was reversed. That is, swapping between *Neutral, Positive, Negative* and *Neutral, Negative,* *Positive*. Entire process for data collection is shown in Figure 3.6. Each subject was also asked to answer the self-reported emotion questionnaire before and after walking for each video. The questions are as follows.

1. Please choose your current feeling: Happy, Sad, Neither (Not Sad and Not Happy)

2. How intense was your feeling: 1 (Very Little) to 5 (Very Much)

3.5 Collected Dataset

There are 49 participants, with 41 men and 8 women. Participants' average age is 19.69 years. The standard deviation of the ages of the participants is 1.40 years. The average height is 168.49 centimeters. The standard deviation of the heights is 6.34 centimeters. The average weight is 58.88 kilograms. The standard deviation of the weights is 10.84 kilograms. Each subject walked around and watched three videos: *Neutral Video, Negative Video, and Positive Video*. In total, there are 147 walking trials. For the order of videos shown to the subjects, 24 subjects watched *Negative Video* before *Positive Video*, and 25 subjects watched *Positive Video* before *Negative Video*.

According to the answers from self-reported emotion questionnaire after finished walking and watching each video, this dataset contains 44 *Sad* walking trials, 44 *Happy* walking trial, and 59 *Neither* walking trials. These emotion tags *(Reported Emotion)* were used in the analysis instead of emotion tag of the videos *(Expected Emotion)* since not all subjects feel *Happy* after watching

Positive Video and not all subjects feel *Sad* after watching *Negative Video*. Table 3.2 shows the numbers of subjects who felt Happy, Sad, and Neither from the self-reported emotion questionnaire for each video stimulus.

Figure 3.8 shows a sample image of a subject walking in a circular pattern in the recording area while watching a video on HoloLens 2, and Figure 3.9 shows a close-up photo of a subject wearing the OptiTrack motion capture suit with 37 markers and walk while watching a video on HoloLens 2.

One of the 147 walking trials was corrupted during recording, so there are 146 usable walking trials. For the direction of walking, there are 99 counter-clockwise walking trials, 21 clockwise walking trials, and 26 walking trials which have both clockwise and counter-clockwise in one walk.

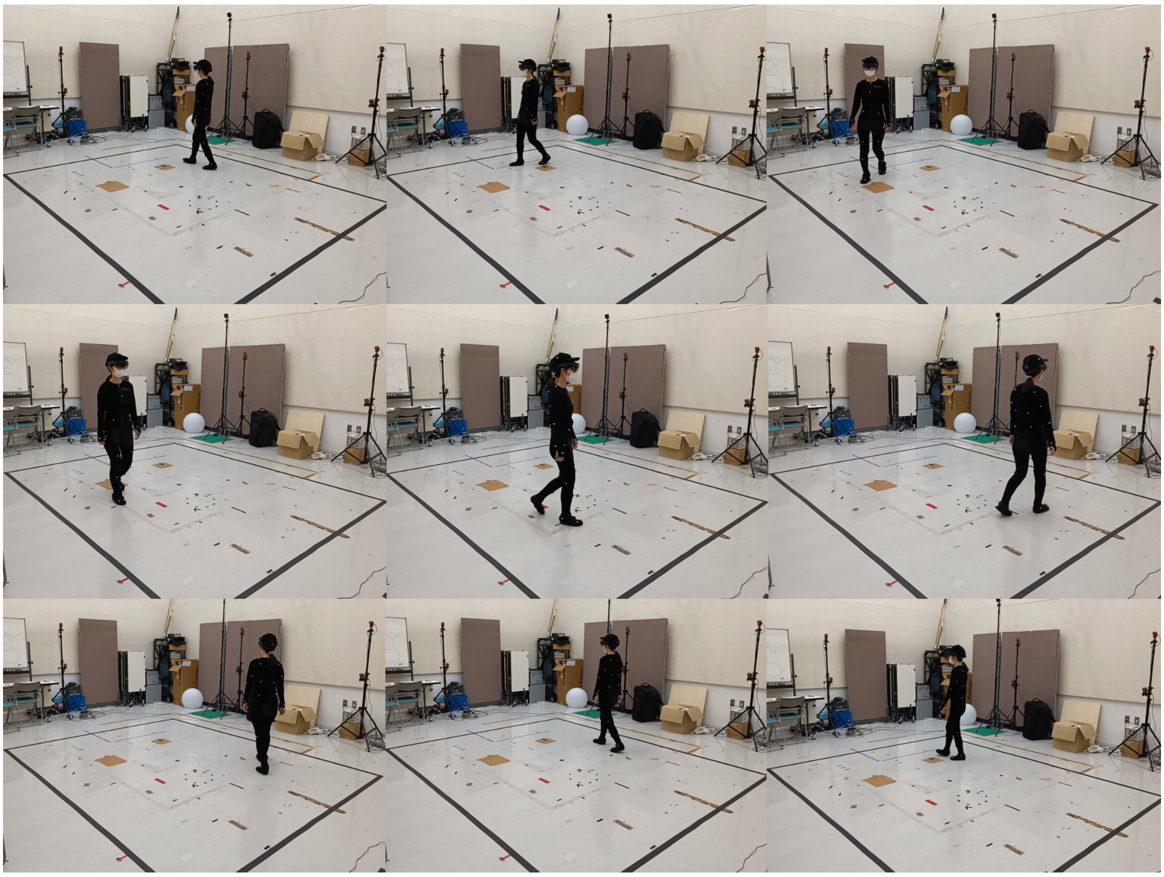

Figure 3.8: Sample of Walking Subject while Watching Video on HoloLens 2

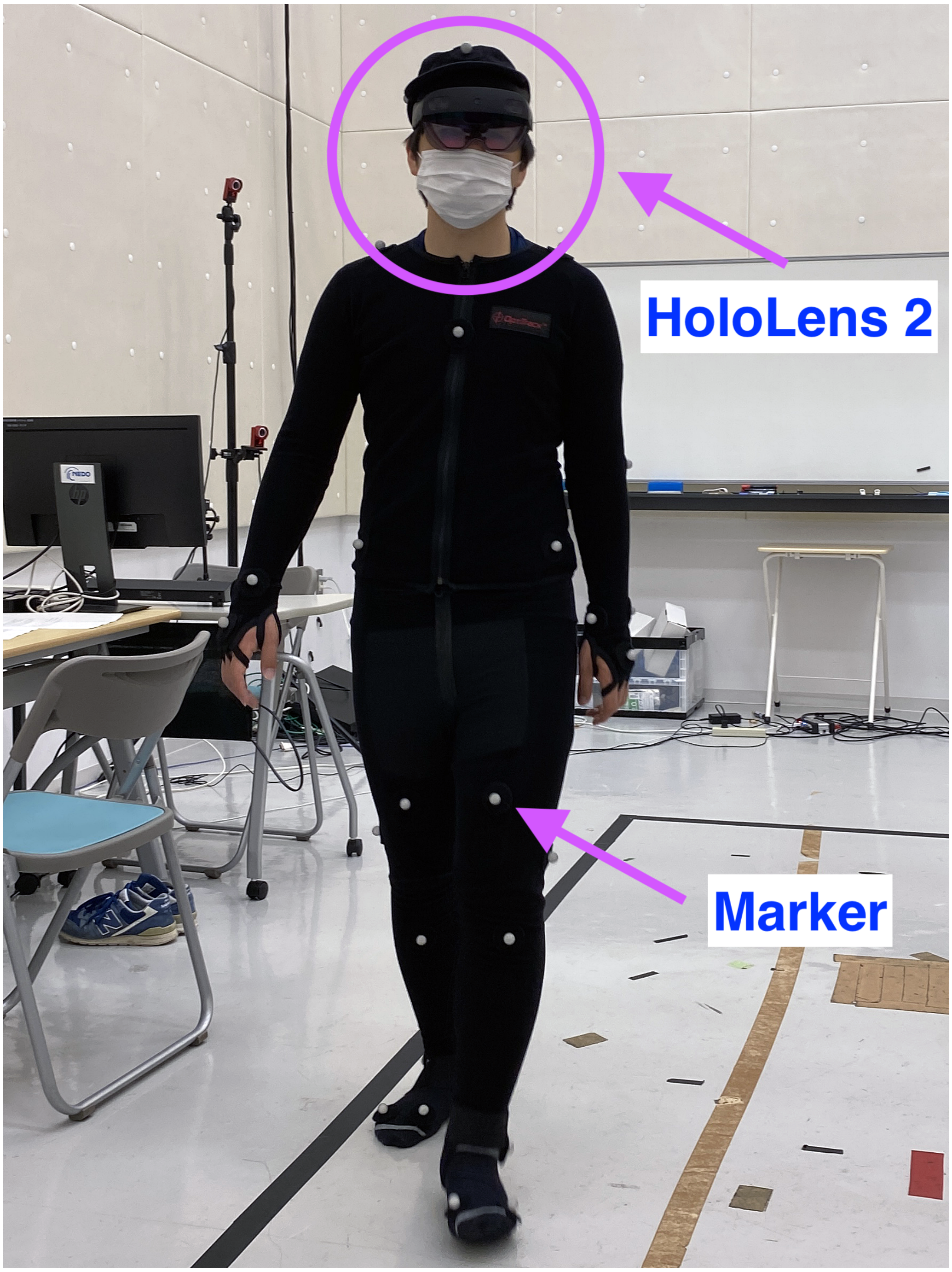

Figure 3.9: A Subject Walking while Watching a Video on HoloLens 2 and Wearing OptiTrack Suit for Motion Capturing

Table 3.1: List of OptiTrack Baseline Markers

HeadTop	
HeadFront	
HeadSide	
BackTop	
Chest	
Back	Left
	Right
WaistFront	Left
	Right
WaistBack	Left
	Right
ShoulderBack	Left
	Right
ShoulderTop	Left
	Right
ElbowOut	Left
	Right
UpperArmHigh	Left
	Right
WristOut	Left
	Right
WristIn	Left
	Right
HandOut	Left
	Right
ThightFront	Left
	Right
KneeOut	Left
	Right
Shin	Left
	Right
AnkleOut	Left
	Right
ToeOut	Left
	Right
ToeIn	Left
	Right

Table 3.2: Comparison of Expected Emotion from Stimuli and Reported Emotion from Self-Reported Questionnaire

Stimuli \Reported Emotion	**Happy**	**Sad**	**Neither**
Positive Movie	12	23	14
Negative Movie	13	19	17
Neutral Movie	19	2	28

Chapter 4

Data Preprocessing

All recorded data can contain meaningful data and noise together. Preprocessing was performed to clean up the data and remove the data which are not meaningful as well as the noise after extracting 3-dimensional coordinates of 37 body markers recorded by OptiTrack from the recorded walking trial.

First, one minute of data was removed from the beginning and the end of each walking trial. Therefore, the initial 6000 frames and the last 6000 frames from each walking trial were removed since the OptiTrack motion recording equipment can capture markers coordinates data at 100 frames per second.

Walking Straightness and *Body Parts Angles* were extracted throughout the feature extraction process. The process of feature extraction is described in Section 5. However, as shown in Figure 4.1, the preprocessing methods for *Walking Straightness* and *Body Parts Angles* are different. The preprocessing steps are described separately below.

After removing first 6000 and last 6000 frames, for *Walking Straightness* feature extraction, the position of *Left Foot* and *Right Foot* were used for straightness calculation. Therefore, each frame was checked whether the coordinates data of *LeftAnkleOut* and *RightAnkleOut* are available. If these two markers data were missing in any frame, that frame was excluded from straightness calculation.

In addition to removing the first and last 6000 frames for *Body Parts Angles* feature extraction, any frame that showed arm movements that were not part of natural walking was also excluded. For example, if the subjects raised their arms to check the time on their watches, or tried to adjust the position of their HoloLens 2 smart glasses, or scratched their heads while walking, these frames were also removed. The Y-coordinates of arm-related markers, such as left and right *HandOut, WristOut, WristIn, and ElbowOut* were checked during this preprocessing stage. For each arm-related marker, mean value and standard deviation value of its Y-coordinate among each walking trial were calculated. If the Y-coordinate in any frame is less than $Mean - 2 \times SD$ or more than $Mean + 2 \times SD$, that frame was removed from the angle calculation.

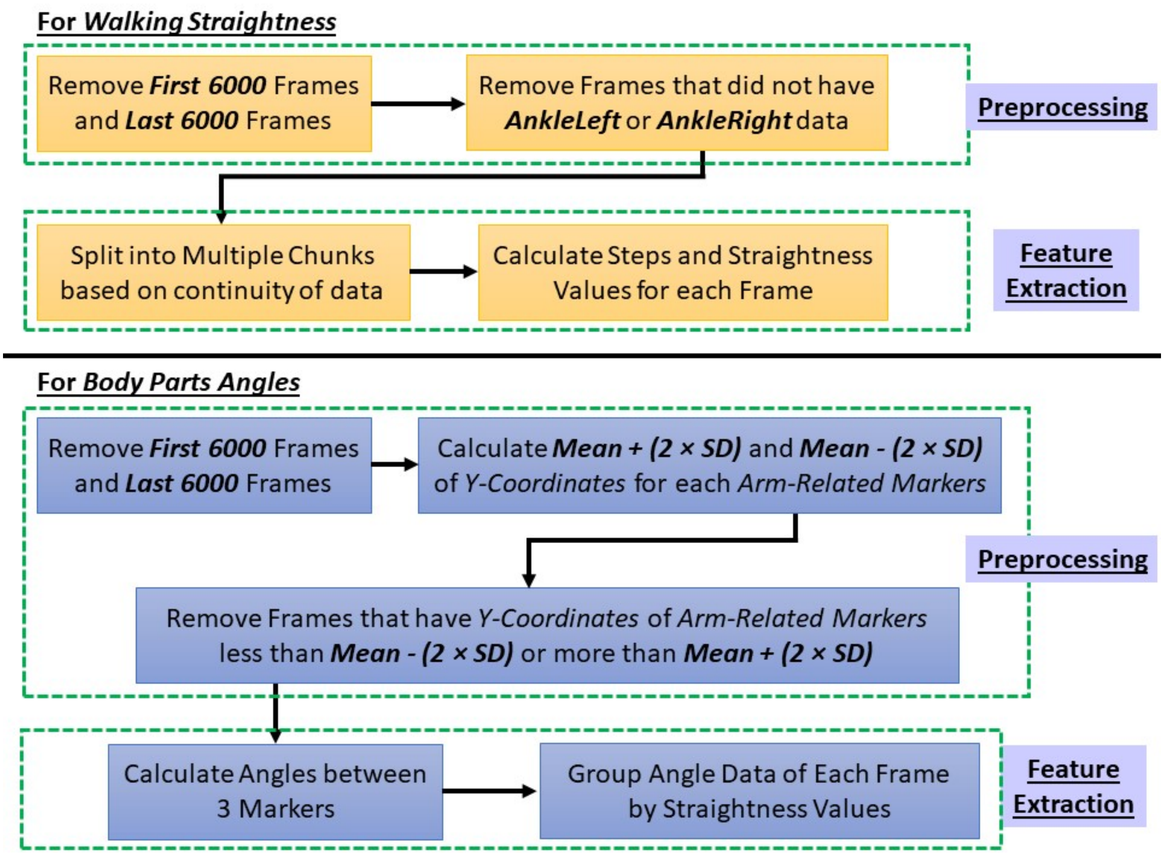

Figure 4.1: Preprocessing Steps for Straightness and Angles

Chapter 5

Feature Extraction

After preprocessing of the coordinate data, there were some missing frames in between each walking trial. As a result, the walking trial is no longer connected. This issue was coped before continuing to the next step by splitting a walking trial into multiple chunks based on the missing frames. If there were more than 25 contiguous missing frames, the next usable frame was split into new walking chunks. However, the next available frames were kept in the same chunk if the length of the missing frames was less than 25 frames. Figure 5.1 shows a diagram of chunk splitting. Any chunk that was less than 50 frames (0.5 second) was discarded because it was too small and unusable.

Walking steps were detected first to calculate the straightness of a walking trial. For each chunk, the distances between the left and right feet in top-view for all frame were calculated. That is, calculating the Euclidean distance between the X and Z coordinates of the left and right feet. The data was then smoothed using the Savitzky-Golay filter before detecting the peaks of distance value from each chunk. Walking steps can be detected by locating peaks in distance between two feet. Any chunk that had fewer than three steps was also discarded.

Straightness of walking in each chunk was computed by using 3 consecutive walking steps. An example diagram of straightness calculation from 3 consecu-

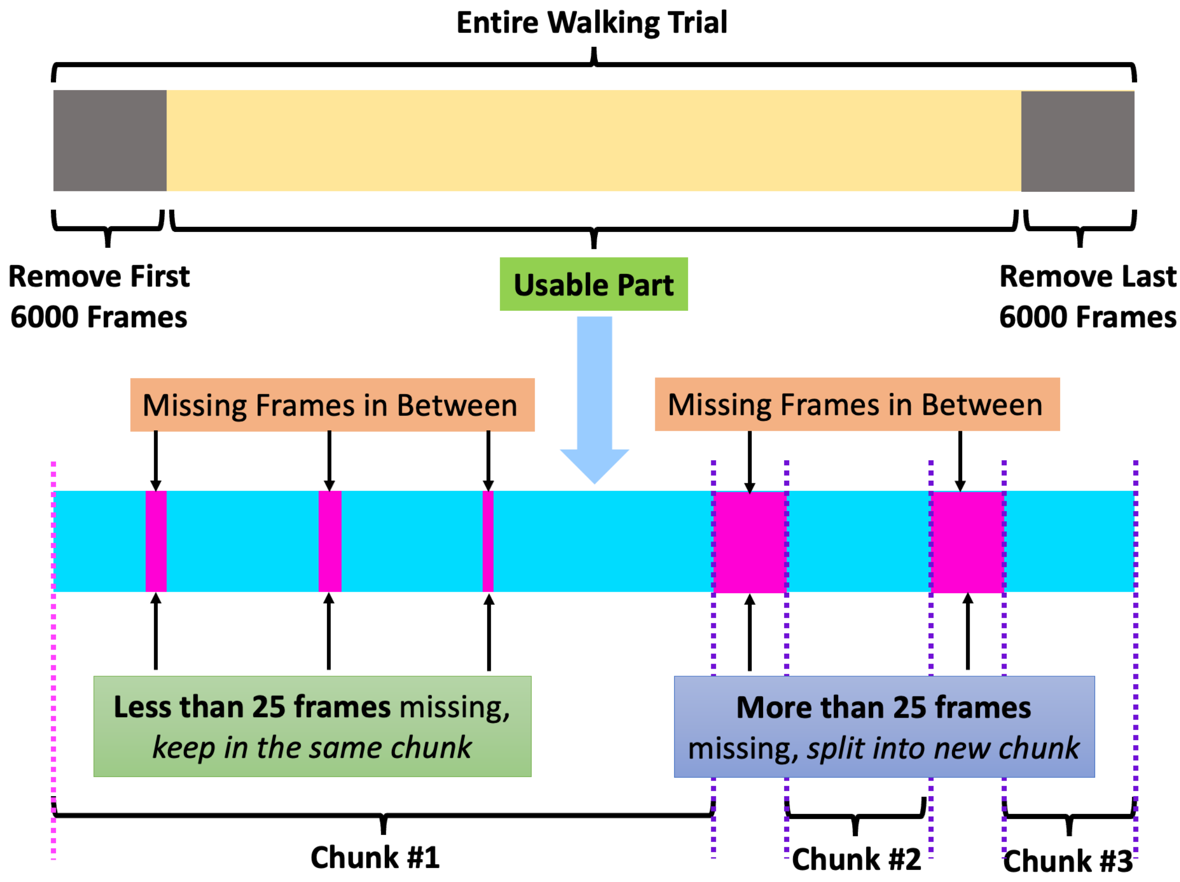

Figure 5.1: Split a Walking Trial into Chunks for Straightness and Angle Calculation

tive steps is shown in Figure 5.2. In this figure, *Step #1* to *Step #2* is the left step, and *Step #2* to *Step #3* is the right step. Therefore, the first straightness value for *Step #1* to *Step #3* is the angle between the vector of left step (*Step #1* to *Step #2*) and right step (*Step #2* to *Step #3*). The detailed process of straightness calculation is as follows.

1. If *Step #1* to *Step #2* is left step, define the left step vector v_{left12} as a vector from (X, Z) point of *Step #1* to (X, Z) point of *Step #2*

2. Define the right step vector $v_{right23}$ as a vector from (X, Z) point of *Step #2* to (X, Z) point of *Step #3*

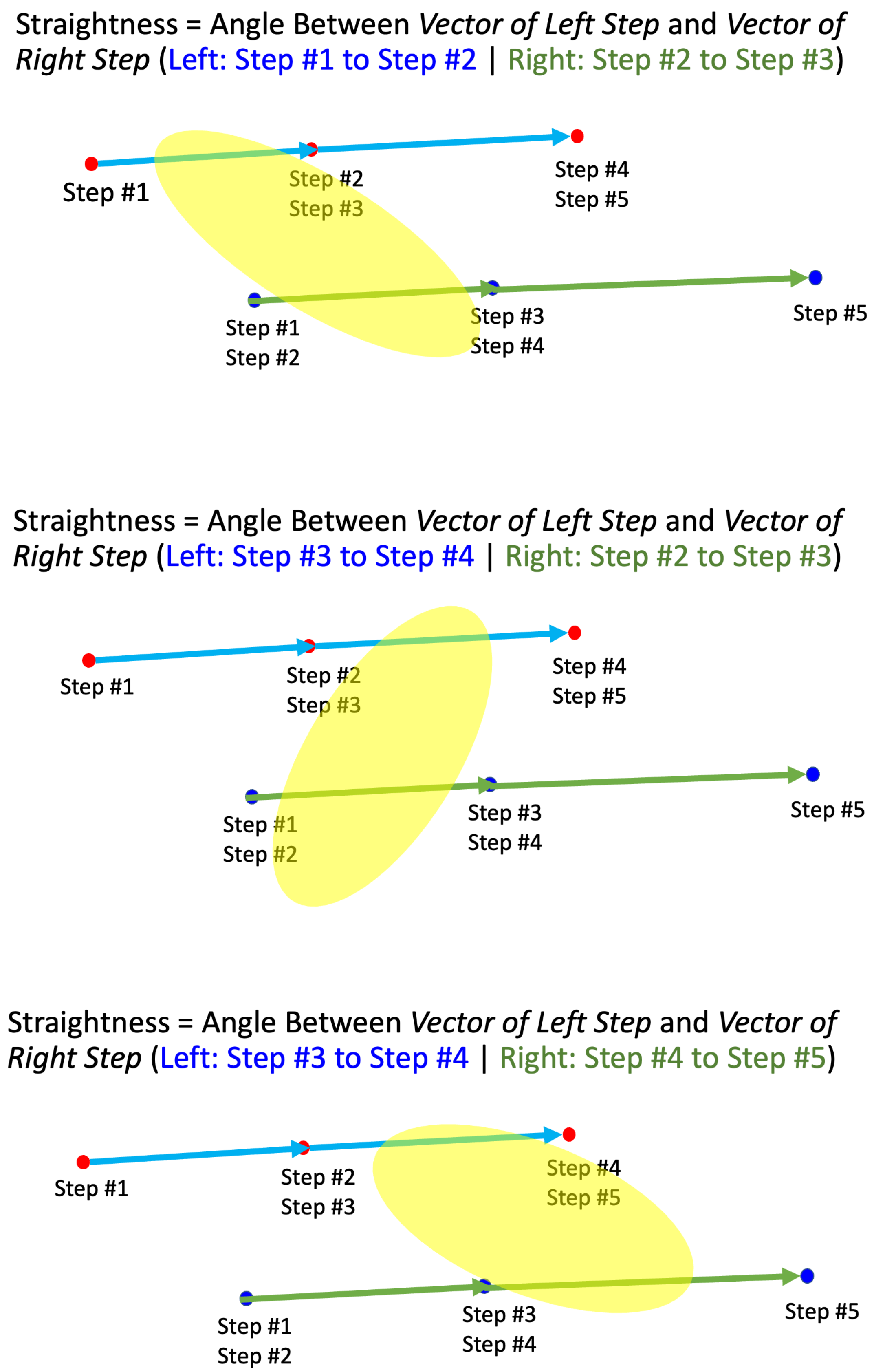

Figure 5.2: Finding Angles between Left and Right Vector to Calculate Straightness

3. **Calculate angle θ_{13} of v_{left12} to $v_{right23}$**

4. Define the next left step vector v_{left34} as a vector from (X, Z) point of *Step #3* to (X, Z) point of *Step #4*

5. **Calculate angle θ_{24} of v_{left34} to $v_{right23}$**

6. Define the next right step vector $v_{right45}$ as a vector from (X, Z) point of *Step #4* to (X, Z) point of *Step #5*

7. **Calculate angle θ_{35} of v_{left34} to $v_{right45}$**

8. If *Step #1* to *Step #2* is right step, vector from (X, Z) point of *Step #1* to (X, Z) point of *Step #2* will be $v_{right12}$, and vector from (X, Z) point of *Step #2* to (X, Z) point of *Step #3* will be v_{left23} instead. This rule applied to all consecutive steps i.e., θ_{13} is angle between $v_{right12}$ to v_{left23}, θ_{24} is angle between $v_{right34}$ to v_{left23} and θ_{35} is angle between $v_{right34}$ to v_{left45}.

9. Continue calculating the angle between left and right vector until finishing each chunk

10. Angle between left and right step vector was used as straightness value of the frames consisting these steps.

After calculating straightness for each 3 consecutive steps, straightness value was assigned to all frames containing these steps. Next, angles between three body part markers were calculated, such as the angle between *LeftShoulderBack* to *LeftUpperArmHigh* and *LeftShoulderBack* to *BackLeft*. As indicated in Table 5.1, a total of 24 angles were calculated from each of the three markers.

In each frame, there are 24 angles and their straightness values. Frames were grouped into 7 straightness groups using their assigned straightness value. These seven straightness groups include one straight walking group and six curved walking group as follows.

- -35° to -25° (Large Curved Walking - Clockwise)
- -25° to -15° (Moderate Curved Walking - Clockwise)
- -15° to -5° (Small Curved Walking - Clockwise)
- -5° to 5° (Straight Walking)
- 5° to 15° (Small Curved Walking - Counter-Clockwise)
- 15° to 25° (Moderate Curved Walking - Counter-Clockwise)
- 25° to 35° (Large Curved Walking - Counter-Clockwise)

However, because 3 consecutive steps were used for computing the straightness values, the frames containing connecting steps between each of 3 consecutive steps always have two straightness values. For instance, the straightness value of *Step #1* to *Step #3* was derived from the angle between *Step #1* and *Step #2* and ***Step #2* and *Step #3***, and the straightness value of *Step #2* to *Step #4* was derived from the angle between ***Step #2* and *Step #3*** and *Step #3* and *Step #4*. Hence, there are two straightness values for the frames containing ***Step #2* to *Step #3***. The average straightness value of *Step #1* to *Step #3* and *Step #2* to *Step #4* was calculated and assigned to these frames. Then, the mean and standard deviation of each angle in each straightness group were then calculated for using in the statistical analyses.

Walking directions of all walking trials were also examined. Because participants were advised to walk in a circular path inside the recording area, but there was no designated path. By analyzing the walking pattern, there are some participants who walked in an excessively curved pattern while others walked in a very straight pattern inside the recording area because each subject chose his or her own path to walk. As a result, in one walking trial, there were multiple walking curvatures, such as straight walking and non-straight (curved) walking. Figure 5.3 shows samples of walking trajectories for six participants. Walking paths of the first two participants are curved and closer to an oval shape, whereas the next two subjects' walking paths are mostly straight with some curved areas only when they turned which seems like a rounded-rectangle shape. The last two participants have very random walking paths with several trajectories and several circle size. As a result, this dataset contains several walking trajectories and curvature which can be defined as *direction-free walking* since the participants were free to select their own walking paths and trajectories in either a clockwise or counter-clockwise direction.

Table 5.1: List of Angles between Each 3 Markers

Angle Index	**Terminal Point #1**	**Initial Point**	**Terminal Point #2**
1	LeftAnkleOut	LeftKneeOut	WaistLeftFront
2	RightAnkleOut	RightKneeOut	WaistRightFront
3	LeftShin	LeftKneeOut	LeftThigh
4	RightShin	RightKneeOut	RightThigh
5	LeftKneeOut	LeftThigh	WaistLeftFront
6	RightKneeOut	RightThigh	WaistRightFront
7	LeftThigh	WaistLeftFront	Chest
8	RightThigh	WaistRightFront	Chest
9	WaistLeftFront	Chest	LeftShoulderTop
10	WaistRightFront	Chest	RightShoulderTop
11	LeftKneeOut	WaistLeftBack	BackLeft
12	RightKneeOut	WaistRightBack	BackRight
13	WaistLeftBack	BackLeft	LeftShoulderBack
14	WaistRightBack	BackRight	RightShoulderBack
15	LeftShoulderBack	BackTop	HeadTop
16	RightShoulderBack	BackTop	HeadTop
17	BackLeft	BackTop	HeadTop
18	BackRight	BackTop	HeadTop
19	BackLeft	LeftShoulderBack	LeftUpperArmHigh
20	BackRight	RightShoulderBack	RightUpperArmHigh
21	BackTop	LeftShoulderBack	LeftUpperArmHigh
22	BackTop	RightShoulderBack	RightUpperArmHigh
23	LeftUpperArmHigh	LeftElbowOut	LeftWristOut
24	RightUpperArmHigh	RightElbowOut	RightWristOut

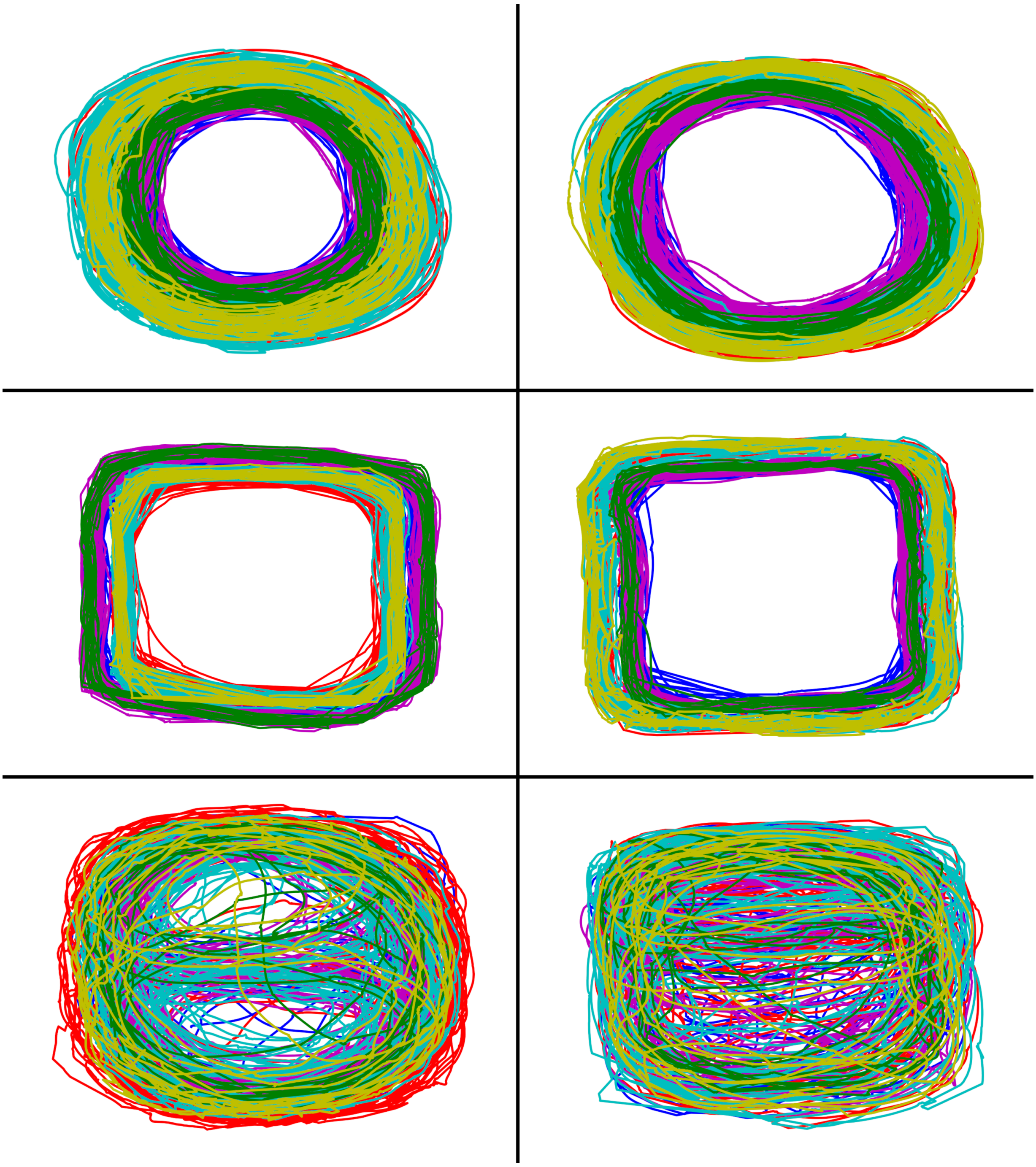

Figure 5.3: Sample of Walking Path for Each Subject

Chapter 6

Statistical Analysis of Gait Features

The following analyses were performed on the mean and standard deviation values of each angle data.

6.1 One-way Analysis of Variance

6.1.1 Methodology

One-way analysis of variance (one-way ANOVA) was performed to check whether emotional differences have effect with movements of each body part when a subject was walking. Both *Expected Emotion* which is the emotion label from video stimuli and *Reported Emotion* which is the emotion label from self-reported questionnaire answers were used.

- **Factor to Test:** Expected Emotion (Positive, Negative, Neutral) and Reported Emotion (Happy, Sad, Neither)
- **Dependent Variable:** Mean value and SD value of each angle in each straightness group

One-way ANOVA was used to compare mean and SD values of all angles in each straightness group for two types of emotions including *Expected Emotion* and *Reported Emotion*. Mean and SD values of angles were compared separately according to their straightness groups in this analysis.

6.1.2 Results

One-way ANOVA was used for checking the effects of *Expected Emotion* and *Reported Emotion* on movements of body parts. Detailed results of ANOVA test on mean and SD of each angle in each straightness group are shown in Table 1 for *Expected Emotion*, and Table 2 for *Reported Emotion*.

According to the significantly different mean and SD of each angle in each straightness group from one-way ANOVA, Tukey Test was then performed for each of them to check which pairs of emotions significantly affected body movements i.e., *Happy vs Sad*, *Neither vs Sad* and *Neither vs Happy*. Table 6.1 and Table 6.2 show all emotion pairs and all angles which have significantly different mean or SD for *Expected Emotion* and *Reported Emotion* respectively.

Table 6.1: Tukey Test Results of Significantly Different Mean and SD of Each Angle in Each Straightness Group (Factor: Expected Emotion)

Straightness Group	**Walking Direction**	**Type**	**Significant Angle Between 3 Markers**	**Significant Pair**	**P-Value from Tukey HSD of Significant Pair**
25°to 35°	Counter-clockwise	SD	RightShoulderBack BackTop HeadTop	Negative Video vs Neutral Video	0.0405

As shown in Table 1 and Table 6.1, in all straightness groups, there is only one SD of angle that is significantly different for *Expected Emotion*. That is, *RightShoulderBack-BackTop-HeadTop* in the 25° to 35°, and the pair that has a significant effect is *Negative Video vs Neutral Video*. Therefore, difference only occurred with high curvature walk in counter-clockwise direction which is the magnitude of head movement between *Negative Video* and *Neutral Video*.

From Table 2, many mean or SD values of angles are significantly different for *Reported Emotion*. Then, Tukey test with each mean or SD value was performed to check which pair of emotions have significantly different body movements. The results of Tukey test are shown in 6.2. In each walking straightness group, at least one mean or SD value of body parts angles was affected by emotional differences, and the SD values of *BackLeft-LeftShoulderBack-LeftUpperArmHigh* are significantly different between *Happy* and *Sad* emotions. The SD value of this angle can be interpreted as *Left Arm Swing Magnitude*. This angle is illustrated in Figure 6.1. According to one-way ANOVA results, the results suggest that *Left Arm Swing Magnitude* is significantly different between *Happy* and *Sad* emotion regardless of walking straightness.

Table 6.2: Tukey Test Results of Significantly Different Mean and SD of Each Angle in Each Straightness Group (Factor: Reported Emotion)

Straightness Group	Walking Direction	Type	Significant Angle Between 3 Markers	Significant Pair	P-Value from Tukey HSD of Significant Pair
-35° to -25°	Clockwise	SD	**BackLeft-LeftShoulderBack-LeftUpperArmHigh**	Happy vs Sad	0.0222
-25° to -15°	Clockwise	Mean	RightAnkleOut-RightKneeOut-WaistRightFront	Happy vs Sad Neither vs Sad	0.0382 0.0070
		SD	WaistLeftFront-Chest-LeftShoulderTop	Happy vs Sad	0.0338
		SD	WaistRightFront-Chest-RightShoulderTop	Happy vs Sad	0.0095
		SD	LeftKneeOut-WaistLeftBack-BackLeft	Happy vs Sad	0.0394
		SD	**BackLeft-LeftShoulderBack-LeftUpperArmHigh**	Happy vs Sad	0.0017
		SD	BackTop-LeftShoulderBack-LeftUpperArmHigh	Happy vs Sad	0.0103
		SD	BackTop-RightShoulderBack-RightUpperArmHigh	Happy vs Sad	0.0018
-15° to -5°	Clockwise	SD	**BackLeft-LeftShoulderBack-LeftUpperArmHigh**	Happy vs Sad	0.0464
		SD	BackTop-LeftShoulderBack-LeftUpperArmHigh	Happy vs Neither	0.0313
-5° to 5°	Straight	SD	**BackLeft-LeftShoulderBack-LeftUpperArmHigh**	Happy vs Sad	0.0258
5° to 15°	Counter-clockwise	SD	**BackLeft-LeftShoulderBack-LeftUpperArmHigh**	Happy vs Sad	0.0250
15° to 25°	Counter-clockwise	Mean	RightShoulderBack-BackTop-HeadTop	Happy vs Sad	0.0405
		Mean	BackTop-LeftShoulderBack-LeftUpperArmHigh	Happy vs Sad	0.0380
		SD	**BackLeft-LeftShoulderBack-LeftUpperArmHigh**	Happy vs Sad Neither vs Sad	0.0088 0.0363
25° to 35°	Counter-clockwise	Mean	RightShoulderBack-BackTop-HeadTop	Happy vs Sad	0.0442
		Mean	BackTop-LeftShoulderBack-LeftUpperArmHigh	Happy vs Sad	0.0342
		SD	**BackLeft-LeftShoulderBack-LeftUpperArmHigh**	Happy vs Sad Neither vs Sad	0.0027 0.0075

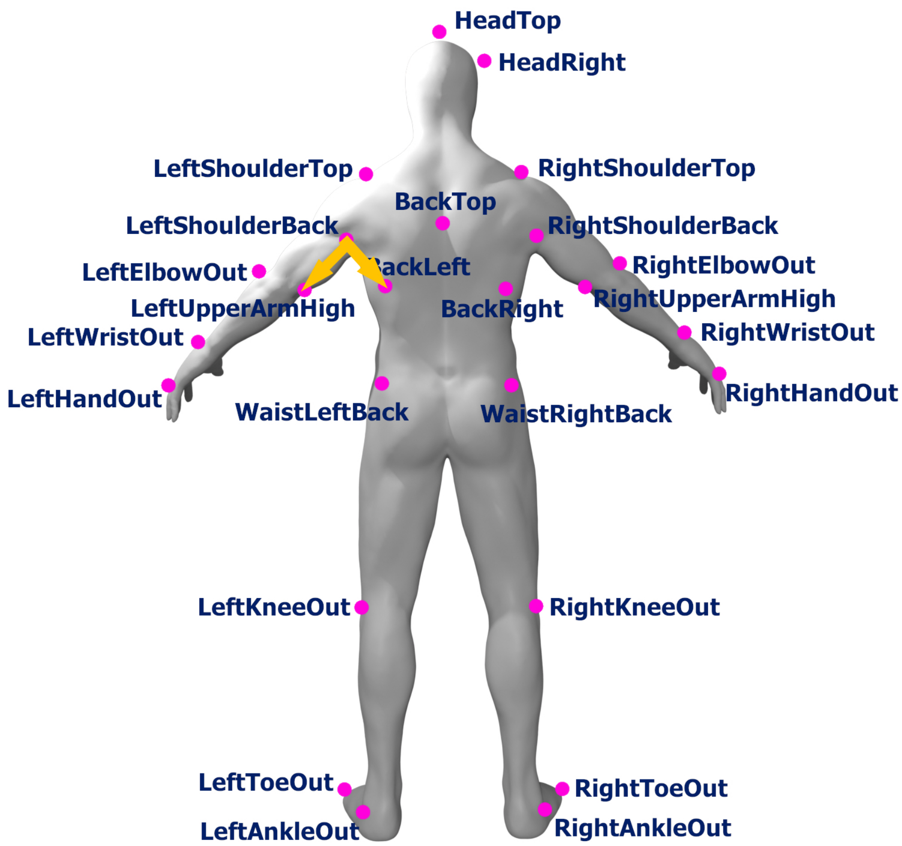

Figure 6.1: Angle of BackLeft-LeftShoulderBack-LeftUpperArmHigh (Arm Swing) in Body Skeleton Image (Original Human Figure Source: dog012 on Sketchfab[2])

As shown in Table 2 and Table 6.2, only left arm swing is significantly different when subjects walk in happy and sad emotions but right arm swing is not. To investigate this issue, inside and outside status of the arm and walking curvature were examined. In circular walking, one arm side is inside while another arm side is outside of the walking path. Relationships between walking curvature and behavior of left and right arm swings as well as inside-outside status of that arm in each emotion were investigated by plotting the arm swing magnitude of the left arm and right arm in all emotions with its curvature level

[2]https://sketchfab.com/3d-models/man-5ae6bd9271ac4ee4905b96e5458f435d

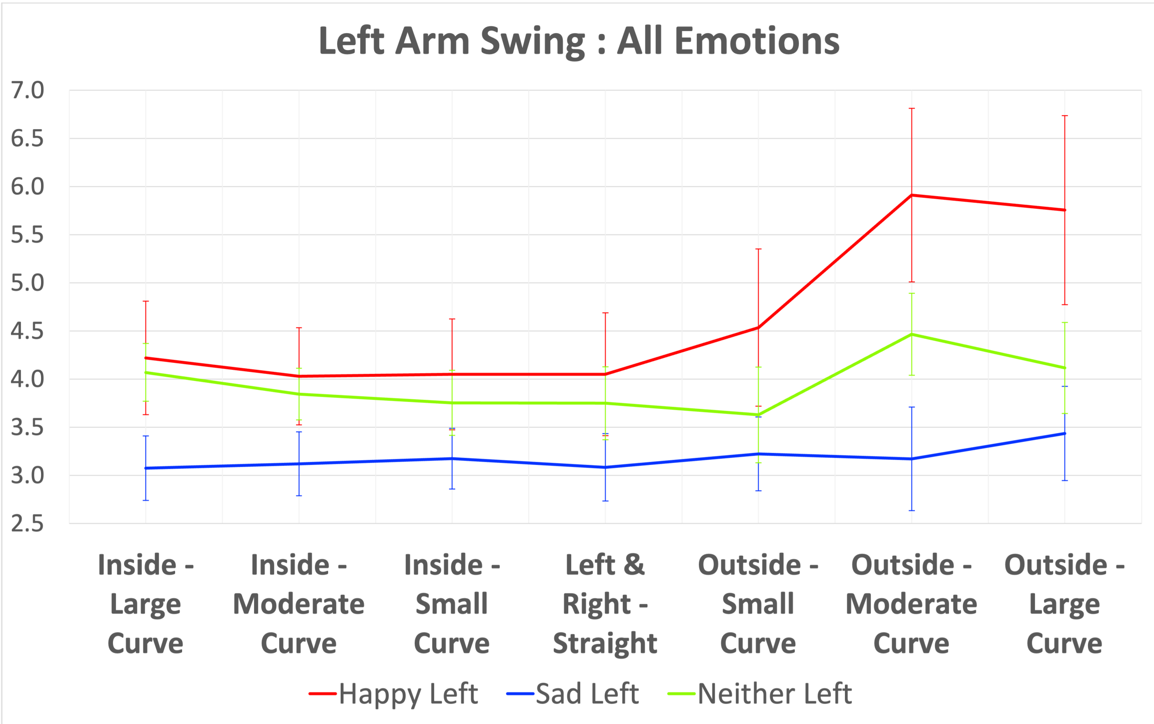

Figure 6.2: Plot of Left Arm Swing in All Emotions (with 95% Confident Interval Error Bars)

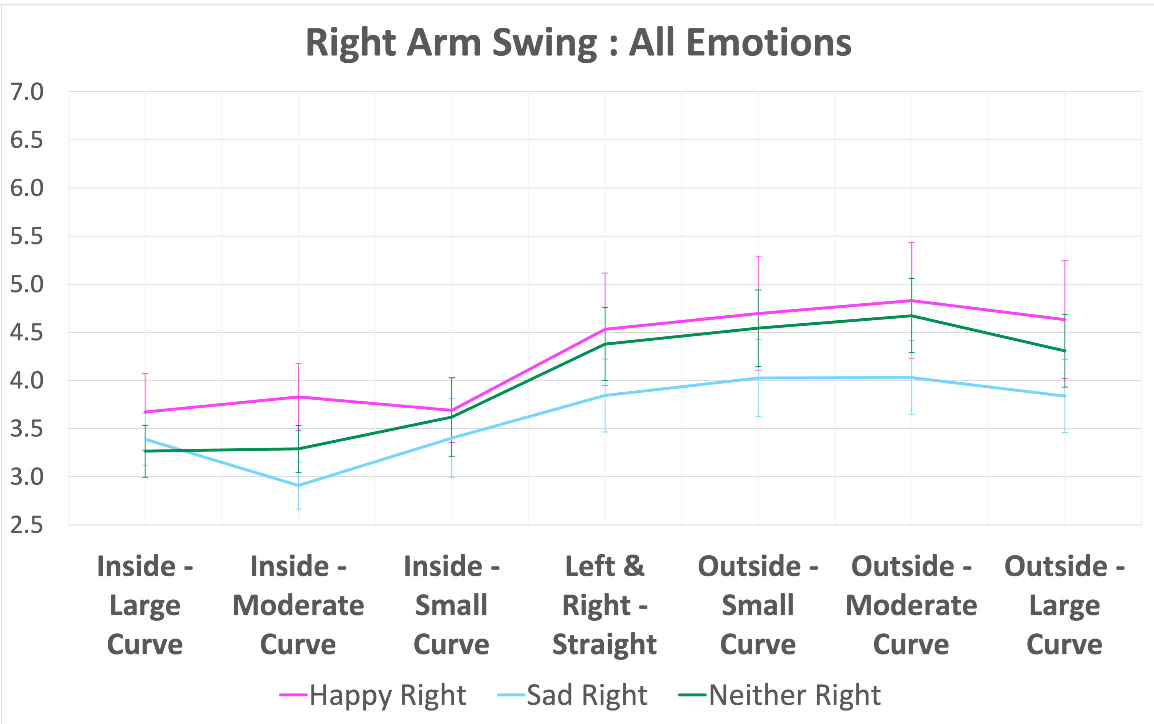

Figure 6.3: Plot of Right Arm Swing in All Emotions (with 95% Confident Interval Error Bars)

and its inside-outside status in Figure 6.2 and Figure 6.3. Walking direction can be used to determined the inside-outside status of each arm i.e., *the left arm is outside and the right arm is inside* when subjects are walking in the *clockwise* direction, and in the *counter-clockwise* direction, *the left arm is inside and the right arm is outside.* For curvature level, it can be determined from the straightness value. If the straightness value is between -35° and -25° or 25° and 35°, it can be considered *large curved walking*, and if the straightness value is -5° to 5°, it can be considered as *straight walking.* For the direction, *minus sign means clockwise*, while *plus sign means counter-clockwise.*

Left arm swing magnitude with its inside-outside status and the curvature level is shown in Figure 6.2. In this figure, when the arm is outside in high curvature walking, there is a large difference between happy and sad. When the curvature decreases, the difference is also reduced but it is still large enough to distinguish between happy and sad emotions. For inside-outside status, the difference between happy and sad is smaller when the arm is inside than when the arm is outside. For right arm swing (Figure 6.3), happy and sad has smaller difference than left arm swing for all curvature levels, but when the right arm is outside in high curvature level, the arm swing is also higher than when the subject walks in a smaller curvature and the right arm is inside.

6.2 Multi-Factor Analysis of Variance

6.2.1 Methodology

Based on the results of one-way ANOVA, *Reported Emotion* has more differences in body movements between emotions than *Expected Emotion*. Result of *Expected Emotion* is listed in Table 6.1 and only one straightness group has significantly different mean or SD of angle. In Table 6.2, *Reported Emotion* has one or more significantly different mean or SD of angles in all straightness groups. Therefore, only *Reported Emotion* is focused from now on.

While analyzing *Reported Emotion*, some straightness groups have several significantly different mean or SD values of angles whereas some straightness groups have only one significantly different mean or SD value of angle. From one-way ANOVA analysis results, the angle named *BackLeft-LeftShoulderBack-LeftUpperArmHigh* has significantly different SD value between *Happy* and *Sad* regardless of curvature level and inside-outside status of the arm.

Multi-factor ANOVA was performed to test several factors including *Reported Emotion*, *Curvature*, *Angle Side*, and combination of these factors. Unlike the one-way ANOVA that was performed separately for each straightness group, multi-factor ANOVA was performed with all straightness groups at once.

For *Reported Emotion*, the arm swing magnitudes were checked whether they are significantly affected by emotions regardless of other factors.

For *Curvature*, the straightness groups were converted to curvature values before performing multi-factor ANOVA. A sign of curvature value (plus or minus) was selected by checking that the left arm and right arm were *Inside* or

Table 6.3: Conversion from Straightness Group to Curvature for Multi-Factor ANOVA (Plus Sign for Outside and Minus Sign for Inside)

Straightness Group	**Actual Side**	**Inside/Outside**	**Resulting Curvature Value**
-35° to -25°	Left	Outside	+30
	Right	Inside	-30
-25° to -15°	Left	Outside	+20
	Right	Inside	-20
-15° to -5°	Left	Outside	+10
	Right	Inside	-10
-5° to 5°	Left	-	0
	Right	-	0
5° to 15°	Left	Inside	-10
	Right	Outside	+10
15° to 25°	Left	Inside	-20
	Right	Outside	+20
25° to 35°	Left	Inside	-30
	Right	Outside	+30

Outside when walking in the circular walking path. For all curved walking groups, *outside arm used plus sign*, and *inside arm used minus sign* as shown in Table 6.3. For straight walking group, the curvature was 0 for both left arm and right arm since there was no inside or outside in straight walk. By checking the *curvature* factor, the curvatures of walking (small curve, moderate curve, large curve) and the status of that left arm and right arm (inside or outside) can be checked that they have a significant effect on arm swing magnitudes or not. As this dataset has circular walking path which is never used in conventional studies, it is useful to explore whether the outside arm swing and inside arm swing when the subjects are walking circularly are symmetric. If left and right arm swings are not symmetric, this means that one side will be clearer to distinguish subjects' current emotion. Also, curvature of walking should be a reason that affect the arm swing.

For *Angle Side*, in one-way ANOVA test, only left arm swing is significantly different between happy and sad emotion. The arm side (left and right) was also checked if it has an effect on arm swing magnitudes or not.

Multi-factor analysis were performed on these factors as follows.

- Reported Emotion: Happy, Sad, Neither
- Curvature: -30, -20, -10, 0 , 10, 20, 30
- Angle Side: Left, Right
- Reported Emotion × Curvature: Happy/-30, Sad/0, Neither/10 etc.
- Reported Emotion × Angle Side: Happy/Left, Happy/Right, Sad/Left, Sad Right etc.
- Curvature × Angle Side: -30/Left, -20/Right, 10/Left etc.
- Reported Emotion × Curvature × Angle Side: Happy/-30/Left, Sad/20/Right etc.

6.2.2 Results

The results of multi-factor ANOVA are shown in Table 6.4. There are some factors which significantly affected arm swing magnitude i.e., *Reported Emotion* and *Walking Curvature*. In addition, interaction effects between *Reported Emotion with Angle Side* and *Walking Curvature with Angle Side* were found.

Tukey test was performed to check the *Reported Emotion* factor. The results from the Tukey test are shown in Table 6.5. According to Table 6.5, all pairs of emotions (*Happy vs Neither*, *Happy vs Sad*, and *Neither vs Sad*) significantly affected arm swing magnitude, regardless of any other factor.

Table 6.4: Results of Multi-Factor ANOVA

Factor	Degrees of Freedom	F-Value	P-Value
Reported Emotion	2	37.6727	**0.0000**
Curvature	6	7.7684	**0.0000**
Angle Side	1	1.8913	0.1693
Reported Emotion × Curvature	12	0.7883	0.6631
Reported Emotion × Angle Side	2	5.3906	**0.0047**
Curvature × Angle Side	6	3.4769	**0.0020**
Reported Emotion × Curvature × Angle Side	12	0.8923	0.5543

Table 6.5: Significantly Different Pairs from Tukey Test of Reported Emotion

Significant Pair	P-Value from Tukey Test
Happy vs Neither	0.0011
Happy vs Sad	0.0000
Neither vs Sad	0.0000

6.3 Linear Regression Analysis

6.3.1 Methodology

Because of the difference between behaviors of left arm swings and right arm swings. That is, the left arm swing is significantly different among emotions while the right arm swing is not. Linear regression analysis was performed with the left arm swings and right arm swings to check if the regression slopes of each arm side are similar or not. The regression equation is as follows.

$$Y = \alpha + \beta \times X \tag{6.1}$$

In this equation, α is the intercept, β is the slope, X is the curvature value, and Y is the predicted arm swing magnitude. In linear regression, α and β values that can minimize the differences between predicted arm swing magnitude ($Y_{Predict}$) and actual arm swing magnitude (Y) for each curvature value were computed for each emotion in each arm side.

The regression equations for left arm swing magnitude in each emotion are as follows.

$$ArmSwing_{HappyLeft} = \alpha_{HappyLeft} + \beta_{HappyLeft} \times Curvature \tag{6.2}$$

$$ArmSwing_{SadLeft} = \alpha_{SadLeft} + \beta_{SadLeft} \times Curvature \tag{6.3}$$

$$ArmSwing_{NeitherLeft} = \alpha_{NeitherLeft} + \beta_{NeitherLeft} \times Curvature \tag{6.4}$$

The regression equations for right arm swing magnitude in each emotion are as follows.

$$ArmSwing_{HappyRight} = \alpha_{HappyRight} + \beta_{HappyRight} \times Curvature \tag{6.5}$$

$$ArmSwing_{SadRight} = \alpha_{SadRight} + \beta_{SadRight} \times Curvature \tag{6.6}$$

$$ArmSwing_{NeitherRight} = \alpha_{NeitherRight} + \beta_{NeitherRight} \times Curvature \tag{6.7}$$

The α and β values of left arm swing and right arm swing for happy, sad, and neither emotion are computed separately. For the left arm, if $\beta_{HappyLeft}$, $\beta_{SadLeft}$, and $\beta_{NeitherLeft}$ are equal, the slopes of all emotions are similar which means that emotional differences have no significant effect with the left arm swing magnitude in each curvature. For the right arm, $\beta_{HappyRight}$, $\beta_{SadRight}$, and $\beta_{NeitherRight}$ are checked whether they are equal. The same rule used for the left arm can be used to check that emotional differences significantly affect the right arm swing or not.

6.3.2 Results

The results of linear regression of each emotion for left arm are as follows.

- Happy: $\alpha = 4.5521$, $\beta = 0.0259$
- Neither: $\alpha = 3.8916$, $\beta = 0.0017$
- Sad: $\alpha = 3.1764$, $\beta = 0.0038$

And for right arm, the results are as follows.

- Happy: $\alpha = 4.2854$, $\beta = 0.0206$
- Neither: $\alpha = 4.0596$, $\beta = 0.0227$
- Sad: $\alpha = 3.6643$, $\beta = 0.0142$

According to these results, for left arm swings, the β values from linear regression of happy and sad are much different ($\beta = 0.0259$ and $\beta = 0.0038$, respectively) which suggest that the left arm swing magnitude when the subjects feel happy is much different from the left arm swing magnitude when the subjects feel sad since the slope of these two emotions are significantly different.

For right arm swings, the β values of happy and sad are also different, but the difference is smaller than that in the left arm swings ($\beta = 0.0206$ and

$\beta = 0.0142$, respectively). Therefore, the right arm swing magnitudes when the subjects feel happy and when the subjects feel sad are also different from each other but the difference is not as much as the left arm.

Additionally, the slope of left arm swings in neither emotion is much different from the slopes of left arm swing in happy and sad emotions ($\beta = 0.0017$). But the slope of the right arm swing in neither emotion is quite similar to the slope of right arm swing in happy emotion ($\beta = 0.0227$). Consequently, arm swing in neither emotion is significantly different compared to happy and sad emotions for the left arm side, but for the right arm side, arm swing in neither emotion is quite similar to arm swing in happy emotion.

In summary, emotional differences largely affected the slopes for the left arm side, but not so much for the right arm side. These results agree with the results of one-way ANOVA.

Chapter 7

Collection of Second Dataset

From all statistical analyses performed, there are some issues that remain unclear. For example, only left arm swing is significantly different in different emotions while right arm swing follows the similar trend but the difference is not significant. Also, the first dataset contains very fewer number of female subjects compared to male subjects. It is a good idea to check if female and male subjects reflect their emotions on arm movement differently. About the asymmetry of left and right body side issue, it can be possible that this issue occurred because of the dominant hand of the subjects. However, the dominant hand data for the first dataset was not collected. Therefore, another dataset which consists of balance numbers of male and female subjects as well as dominant hand data was collected for further investigation.

7.1 Data Collection Methods

The second dataset was collected with similar procedures as the first dataset mentioned in Chapter 3. The dominant hand, dominant foot, and dominant brain side data were collected to be used for checking if these factors affect with the arm movements of left and right body side. Questionnaires for collection of these additional data and their results are described in Section 7.1.1.

7.1.1 Collected Dataset

In this dataset, university students were recruited to participate in the experiments. There are 10 male and 13 female subjects. The average age of all subjects is 19.91 years with 3.04 years standard deviation. The average height among all subjects are 164.93 centimeters. The standard deviation of the heights is 9.58 centimeters. The average weight of subjects is 57.32 kilograms with 11.32 kilograms standard deviation.

Dominant hand data of participants were collected using the modified version of Flinders Handedness survey questions published by Left Handers Association of Japan to make the questions more appropriate with Japanese culture. The dominant hand or handedness checking questions are available at `https://lefthandedlife.net/faq003.html`. These questions are in Japanese language so the participants can understand easily. The questions in Japanese and their English translations are as follows.

1. 文字を書くとき、どちらの手でペン（筆記具）を持ちますか？

   When writing, which hand do you hold a pen (writing instrument)?

2. 食事をするとき、どちらの手でスプーンを持ちますか？

   When you eat, which hand do you hold the spoon?

3. 歯を磨くとき、どちらの手で歯ブラシを持ちますか？

   When brushing your teeth, which hand do you hold your toothbrush?

4. マッチを擦るとき、どちらの手でマッチ棒を持ちますか？

   When you rub a match, which hand do you hold the matchstick?

5. 消しゴムで文字や図画を消すとき、どちらの手で消しゴムを持ちますか？

   When erasing letters and drawings with an eraser, which hand do you hold the eraser?

6. お裁縫をするとき、どちらの手で縫い針を持ちますか？

   When sewing, which hand do you hold the sewing needle?

7. 食卓でパンにバターを塗るとき、どちらの手でナイフを持ちますか？

   When you put butter on bread, which hand do you hold the knife?

8. 釘を打つとき、どちらの手で金づち（ハンマー）を持ちますか？

   When you hit a nail, which hand do you hold the hammer?

9. ジャガイモやりんごの皮をむくとき、どちらの手でピーラー (皮むき器) を持ちますか？

   When peeling potatoes or apples, which hand do you hold the peeler?

10. 絵を描くとき、どちらの手で絵筆やペンを持ちますか？

    When drawing, which hand do you hold the paintbrush or pen?

From these questions, handedness point was calculated as -1 for using left hand, +1 for using right hand and 0 for using both hands. If the total point is -10 to -5, that subject is left-handed person. If the total point is -4 to +4, that subject is both-handed person, and if the total point is +5 to +10, that subject is right-handed person. In this dataset, there are 10 left-handed subjects, 8 right-handed subjects and 5 both-handed subjects.

Moreover, the dominant foot data of all participants were also collected using Chapman et al.' Foot Dominant test questions. These questions are available in Japanese language at https://blog.goo.ne.jp/lefty-yasuo/e/37149f8d3105e9b43aa58c5925024915. In this data collection, Japanese language questions were used together with their English translations so all Japanese subjects can understand all questions completely and easily. The foot dominant test questions are as follows.

1. サッカーボールを蹴る

   Which foot do you use to kick a soccer ball?

2. 缶を踏みつける

   Which foot do you use for trampling the can?

3. ゴルフボールを迷路に沿って転がす

   Which leg do you use to roll a golf ball along the maze?

4. 砂に足で文字を書く

   Which foot do you use to write letters on the sand?

5. 砂地をならす

   Which foot do you use to smooth the sand?

6. 小石を足で並べる

   Which foot do you use to arrange the pebbles?

7. 足先に棒を立てる

   Which foot do you use to put a stick on your toes?

8. ゴルフボールを円に沿って転がす

   Which foot do you use to roll the golf ball along the circle?

9. 片足跳びをできるだけ速くする

   Which foot do you use to make one-legged jumps as fast as possible?

10. できるだけ高く足を蹴上げる

    Which foot do you use to kick up as high as you can?

11. 足先でこつこつリズムをとる

    Which foot do you use to take a rhythm?

The dominant foot score can be calculated by checking the foot that the subjects used in each question. Left foot has 3 points, right foot has 1 point and both feet has 2 points. If the total score of foot dominant is 28 points or more, the subject is left-footed person, and if the total score is less than 28 points, that subject is right-footed person. In this dataset, there are 8 left-footed subjects and 15 right-footed subjects.

Brain dominance can be another cause of asymmetric body movements in different emotions. Arm and hand folding brain test method was selected from variety of dominant brain side test methods publicly available on the Internet. The subjects chose the pictures which are matched with their arm and hand folding methods available at `https://www.lettuceclub.net/news/article/194896/`. Questions were shown in Japanese language as follows.

1. 自然に腕を組んでください。どのようになりましたか？

   Please fold your arm naturally. Which picture matches with you?

2. 自然に手を組んでください。どのようになりましたか？

   Please fold your hand naturally. Which picture matches with you?

Each question also has arm and hand folding examples so the subjects can understand easily. These examples are shown in Figure 7.1. Hand folding test is for testing the input brain, and arm folding test is for testing the output brain. When folding the hand, if the thumb of the right hand is below the thumb of the left hand, that subject has right-brained input. If the thumb of the left hand is below, that subject has left-brained input. When folding the arm, if the right arm is under the left arm, that subject has right-brained output, and if the left arm is below, that subject has left-brained output. This dataset contains 3 left-input/left-output, 7 left-input/right-output, 7 right-input/left-output and 6 right-input/right-output dominant brain side subjects.

As walking while watching videos on HoloLens 2 at the same time can distract some subjects from walking naturally, this dataset also has a question asking all participants that whether they can walk naturally while watching videos on HoloLens 2. The results of this questions are 7 subjects answered they can walk naturally, 8 subjects answered they cannot walk naturally and 8 subjects answered they are not sure. The results of this questions in Japanese with their English translation are as follows.
7 subjects who answered they can walk naturally explained as follows.

- 映像に集中していたから。

  Because I was concentrating on the video

[1]https://www.lettuceclub.net/news/article/194896/

Figure 7.1: Arm and Hand Folding Examples(Image Source: Lettuce Club[1])

- 映像を見ることに集中していたため

  Because I was concentrating on watching the video

- 映像に集中していたから

  Because I was concentrating on the video

- 動画に集中していたから

  Because I was concentrating on the video

- 歩きにくさを感じなかったから

  Because I did not find it difficult to walk

- 飽きなかったから！

  I did not get tired of it!

- 視界が完全に隠されてたわけではなかったため。あしもとは見えてたので比較的歩きやすかった。

  Because the view was not completely hidden. I could see the foot, so it was relatively easy to walk.

8 subjects who answered they cannot walk naturally explained as follows.

- 音や映像に気を取られたから

  Because I was distracted by the sound and images

- 途中でフラついたり、まっすぐ歩けなかったりしたからです。

  Because I was fluttering on the way and I could not walk straight

- Because I need to concentrate while watching the movie, as well as paying attention to not to walk crossing the black border.

- 映像に集中していたから

  Because I was concentrating on the video

- 映像に集中していて、たまに枠線を超えそうになったから。

  Because I was concentrating on the video and sometimes I almost crossed the border

- 歩く範囲が小さいため

  Because the walking range is small

- 歩くことと見ることの二つのことに集中していたので自然に歩いていなかったと思う。

  I think I did not walk naturally because I was concentrating on two things, walking and seeing.

- 途中で酔ってしまい、回数を重ねるにつれて歩くことが辛くなってきたため。

  I got drunk on the way, and it became difficult to walk as the number of times increased.

8 subjects who answered they were not sure that they can walk naturally or not explained as follows.

- 時々眠たかったから

  Sometimes, I wanted to sleep.

- 歩き方をあまり意識してなかったから

  Because I was not really conscious of how to walk

- 映像を見ながら歩くのが少し難しかった

  It was a little difficult to walk while watching the video.

- 映像に集中していた

  I was concentrating on the video.

- 枠外には出なかったが、円状を単調に歩いていたので、目がくらんで、不自然に歩いていたかもしれないから。

  I did not go out of the frame, but I was walking monotonously in a circle, so I might have been dazzled and walked unnaturally.

- 何も考えていなかったため、自然だったかはわからないです

  I did not think about anything, so I do not know if it was natural.

- 自分がどう歩いていたか気にしていなかった

  I did not care how I was walking.

- ・疲れていた・靴が気になった・円に沿って歩くことに集中していた

  I was tired. / I was worried about my shoes. / I was concentrating on walking along the circle.

In total, this dataset contains walking trials from 23 subjects walking while watching three emotion-inducing videos. Therefore, 69 walking trials were collected. After finishing each walk, each subject was asked to answer the self-reported emotional questionnaire for checking how did they feel using the same questions as used in the first dataset collection. In this dataset, there are 22 happy walking trials, 29 sad walking trials and 18 neither walking trials. Comparison between *Expected Emotion* and *Reported Emotion* is shown in Table 7.1.

Table 7.1: Comparison of Expected Emotion from Stimuli and Reported Emotion from Self-Reported Questionnaire for the Second Dataset

Stimuli \Reported Emotion	**Happy**	**Sad**	**Neither**
Positive Movie	10	7	6
Negative Movie	0	19	4
Neutral Movie	12	3	8

Chapter 8

Data Proprocessing and Feature Extraction of Second Dataset

Walking trials in the second dataset were preprocessed using the same procedure with the first dataset explained in Chapter 4. Features extraction was also done using the same method as described in Chapter 5.

In this dataset, walking directions of all trials from each subject were also checked in the same way as the first dataset. Figure 8.1 shows six examples of walking paths from six subjects. This dataset contains similar walking trajectories like the first dataset including oval shape, rounded-rectangle shape, and random walking paths.

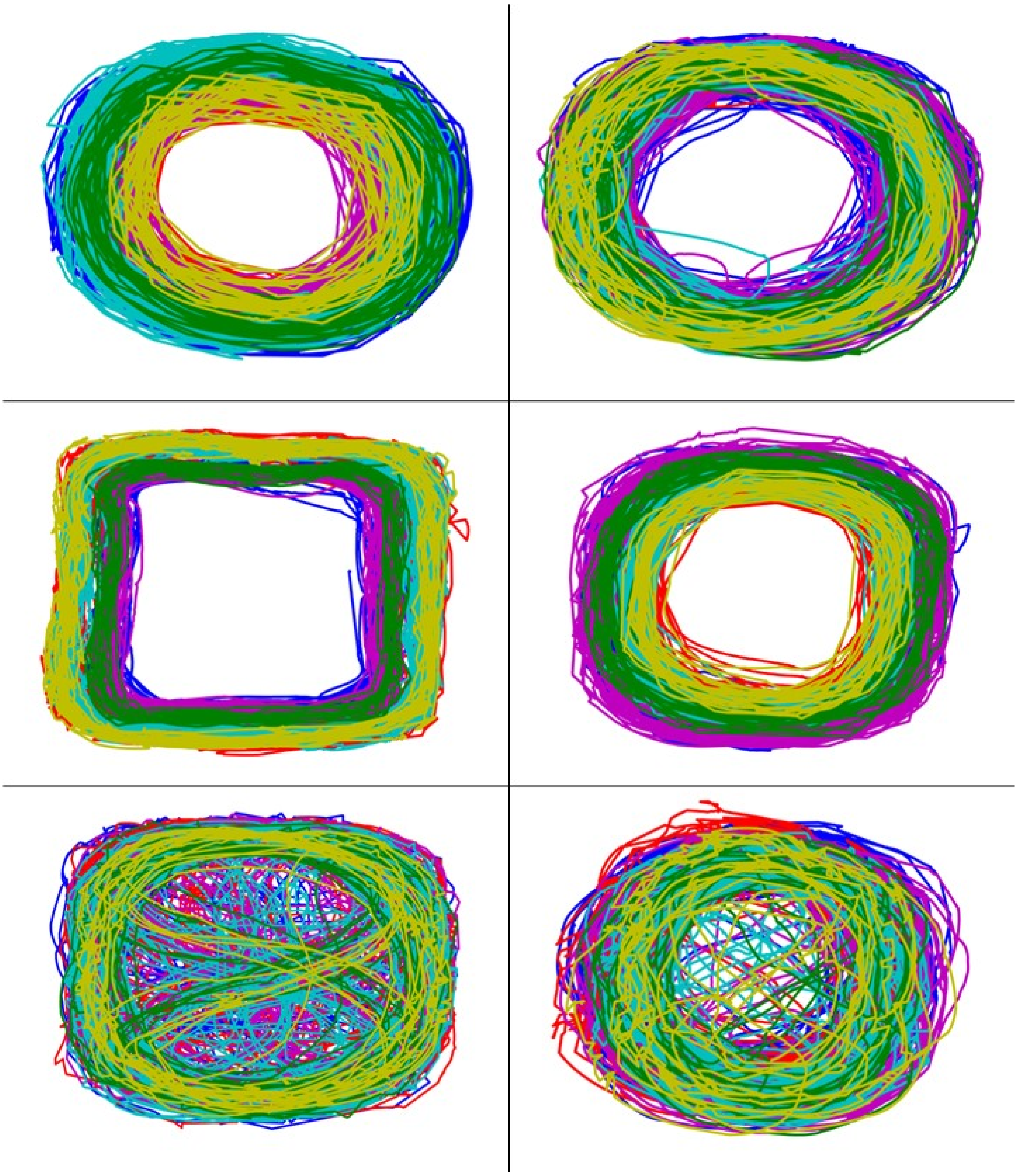

Figure 8.1: Sample of Walking Path for Each Subject in the Second Dataset

Chapter 9

Statistical Analysis of Gait Features for the Combination of Both Datasets

Because the second dataset contains only 23 subjects, it is too small to be used alone for further analyses. As the second dataset was collected using the same method as used in the first dataset collection, both datasets can be combined together to be used in the remaining analyses. The combination of two datasets contain 72 subjects in total. In the combined dataset, the average age of all subjects is 19.76 years. The standard deviation of subjects' age is 2.05 years. The average height is 167.35 centimeters with 7.64 centimeters standard deviation. The average weight is 58.38 kilograms, and the standard deviation of the weight is 10.94 kilograms. There are 51 male subjects and 21 female subjects after combining the two datasets.

9.1 One-way Analysis of Variance

9.1.1 Methodology

One-way analysis of variance (ANOVA) was performed with both *Expected Emotion* and *Reported Emotion* to find the effects of emotional differences to body parts movements in each straightness group separately using the same procedure which were applied with the first dataset as described in Section 6.1.

9.1.2 Results

One-way ANOVA was performed to check the effects of emotional differences for *Expected Emotion* and *Reported Emotion* in each straightness group. Results of one-way ANOVA of the combined dataset are shown in Table 3 and Table 4 for *Expected Emotion* and *Reported Emotion* respectively.

From the results of *Expected Emotion* analysis in Table 3, there is one significantly different angle among different expected emotions from video stimuli. That angle is *BackLeft-LeftShoulderBack-LeftUpperArmHigh* and the statistical value that is significantly different is the standard deviation in 25° to 35° straightness group. Hence, the result suggests that arm swing magnitudes are different when the subjects walked and watched different emotional videos in highly curved walking. Unfortunately, emotion induction results which are shown in Table 7.1 and Table 3.2 for both datasets reveal that some subjects did not feel the emotion they were expected to feel; therefore, it will not be accurate to rely on the expected emotions annotated from the videos. Using *Reported Emotion* they answered from the self-reported questionnaire after finishing each walk should be better and more accurate to compare the subjects movements corresponding to their emotions. The remaining analyses are focused on *Reported Emotion* instead.

In *Reported Emotion* analysis, the results of one-way ANOVA are shown in Table 4. From this table, there are several mean and SD values of angles which are significantly different among different *Reported Emotion*. However, many mean or SD values of angles are different between happy emotion and neither emotion, as well as neither emotion with sad emotion. Neither emotion should not be mainly considered due to its randomness because neither means any other emotions which are not happy and sad that subjects felt after walking. Consequently, only differences between happy and sad emotions are considered and discussed.

In the combined dataset results (Table 9.1), there are only two straightness groups i.e., -25° to -15° and 25° to 35° which have significantly different arm swing magnitudes between happy and sad emotions. However, in the first dataset containing 49 subjects, left arm swing magnitude is significantly different in all straightness groups as shown in Table 6.2.

Table 9.1: Tukey Test Results of Significantly Different Mean and SD of Each Angle in Each Straightness Group for the Combined Dataset (Factor: Reported Emotion)

Straightness Group	**Walking Direction**	**Type**	**Significant Angle Between 3 Markers**	**Significant Pair**	**P-Value from Tukey HSD of Significant Pair**
-35° to -25°	Clockwise	SD	BackTop-RightShoulderBack-RightUpperArmHigh	Happy vs Neither	0.0053
				Happy vs Sad	0.0055
-25° to -15°	Clockwise	Mean	RightKneeOut-WaistRightBack-BackRight	Happy vs Neither	0.0289
			WaistRightBack-BackRight-RightShoulderBack	Happy vs Neither	0.0279
		SD	**BackRight-RightShoulderBack-RightUpperArmHigh**	Happy vs Sad	0.0106
		SD	BackTop-RightShoulderBack-RightUpperArmHigh	Happy vs Sad	0.0095
-15° to -5°	Clockwise	Mean	BackTop-RightShoulderBack-RightUpperArmHigh	Happy vs Sad	0.0323
		SD	BackLeft-BackTop-HeadTop	Happy vs Sad	0.0392
-5° to 5°	Straight	Mean	LeftKneeOut-WaistLeftBack-BackLeft	Happy vs Neither	0.0321
		Mean	RightKneeOut-WaistRightBack-BackRight	Happy vs Neither	0.0134
		Mean	WaistRightBack-BackRight-RightShoulderBack	Happy vs Neither	0.0384
		SD	RightThigh-WaistRightFront-Chest	Happy vs Neither	0.0420
5° to 15°	Counter-clockwise	Mean	RightKneeOut-WaistRightBack-BackRight	Happy vs Neither	0.0185
		Mean	LeftKneeOut-WaistLeftBack-BackLeft	Happy vs Neither	0.0356
		Mean	WaistRightBack-BackRight-RightShoulderBack	Happy vs Neither	0.0230
15° to 25°	Counter-clockwise	Mean	LeftKneeOut-WaistLeftBack-BackLeft	Happy vs Neither	0.0223
		SD	LeftAnkleOut-LeftKneeOut-WaistLeftFront	Neither vs Sad	0.0318
25° to 35°	Counter-clockwise	SD	**BackLeft-LeftShoulderBack-LeftUpperArmHigh**	Happy vs Sad	0.0084
				Neither vs Sad	0.0059

To investigate this issue, left and right arm swing magnitudes when subjects feel happy and when subjects feel sad were compared for the combined dataset in each straightness group separately as shown in Table 9.2. In this table, although the P-Values of ANOVA are not significantly different in all straightness groups unlike the first dataset, all arm swing magnitudes in happy emotion for both left arm and right arm are higher than arm swing magnitudes in sad emotion. Therefore, the results reveal that arm swing magnitudes in the combined dataset are also different in the similar way as the first dataset, and they are good indicators for checking subjects' emotions while walking.

Table 9.2: Comparison of Arm Swing Magnitude (SD) in All Emotions for Left and Right Side

Straightness Group	Actual Side	Inside-Outside	Happy	Neither	Sad	P-Value
-35° to -25°	Left	Outside	4.7397	4.1201	4.1201	0.0946
	Right	Inside	3.1135	2.9016	2.5081	0.1402
-25° to -15°	Left	Outside	4.5419	4.0405	3.8495	0.6368
	Right	Inside	3.2592	2.9839	2.3355	**0.0108**
-15° to -5°	Left	Outside	3.8775	3.9309	3.6233	0.8838
	Right	Inside	3.2077	3.2726	2.7860	0.1391
-5° to 5°	Left	-	3.5731	4.0528	3.3611	0.4307
	Right	-	4.0320	4.1392	3.9359	0.9518
5° to 15°	Left	Inside	3.6771	3.7567	2.9633	0.0949
	Right	Outside	4.2459	4.3586	3.6563	0.1557
15° to 25°	Left	Inside	3.7112	3.6912	3.1002	0.1161
	Right	Outside	4.4104	4.6158	3.9949	0.4638
25° to 35°	Left	Inside	3.8690	3.8837	2.8686	**0.0023**
	Right	Outside	4.3145	3.9962	3.6108	0.1645

Besides, in the first dataset, relationship between arm swing magnitudes with their inside-outside statuses and their walking curvature levels were analyzed by plotting those values in each curvature level including small, moderate, and large curved walking. In the combined dataset, similar plots were performed. Figure 9.1 and Figure 9.2 show the arm swing magnitudes (SD of *BackRight-*

RightShoulderBack-RightUpperArmHigh and SD of *BackLeft-LeftShoulderBack-LeftUpperArmHigh*) when each arm is inside and outside of the circular walking path in different curvature levels for all emotions.

In Figure 9.1, the left arm swing magnitude increases when the walking curvature increases for happy emotion. Also, when the left arm is outside, the movement of this arm is higher compared to when this arm is inside. For sad emotion, the left arm swing magnitude also increases when the arm is outside and the curvature of walking increases. However, when the left arm is inside, curvature level does not affect much with arm swing magnitude. That is, when the curvature level changes, if the left arm is inside, left arm swing magnitude slightly changes. But if the left arm is outside, left arm swing magnitude increases a lot when the curvature is larger. For the differences between happy and sad arm swing magnitudes, the combined dataset has smaller differences in comparison to the first dataset. In some conditions such as large curvature level walk, the difference is high so it is easy to distinguish between happy and sad. But in some other conditions such as when the subjects walk straight, the difference is smaller so it will be more difficult to determine that subjects are feeling sad or happy.

Figure 9.2 shows the right arm swing magnitude according to its inside-outside status and the curvature level. In this plot, difference between right arm swing magnitudes of happy and sad emotion is smaller than the left arm. About the walking curvature and inside-outside status, arm swings in both happy and sad increase when the right arm is outside of the circular walking path compared to when the right arm is inside. Also, when the curvature level is larger in outside conditions, the arm swing magnitudes increase, but when the curvature level changes in inside conditions, arm swing magnitudes do not change much. Therefore, the plots for the right arm is quite similar to the left arm, and the differences between happy and sad emotions can be distinguished easier on the left arm.

In summary, differences between the arm swing magnitudes in different emotions of the left arm are larger than the right arm. The arm swing also increases when the curvature level increases and that arm is outside arm. These results agree with the result from previous dataset as shown in Figure 6.2 and Figure 6.3. We can imply that the left arm swing magnitudes reveal subjects' emotion better than the right arm swing magnitudes, especially when the left arm is outside and the walking curvature is large.

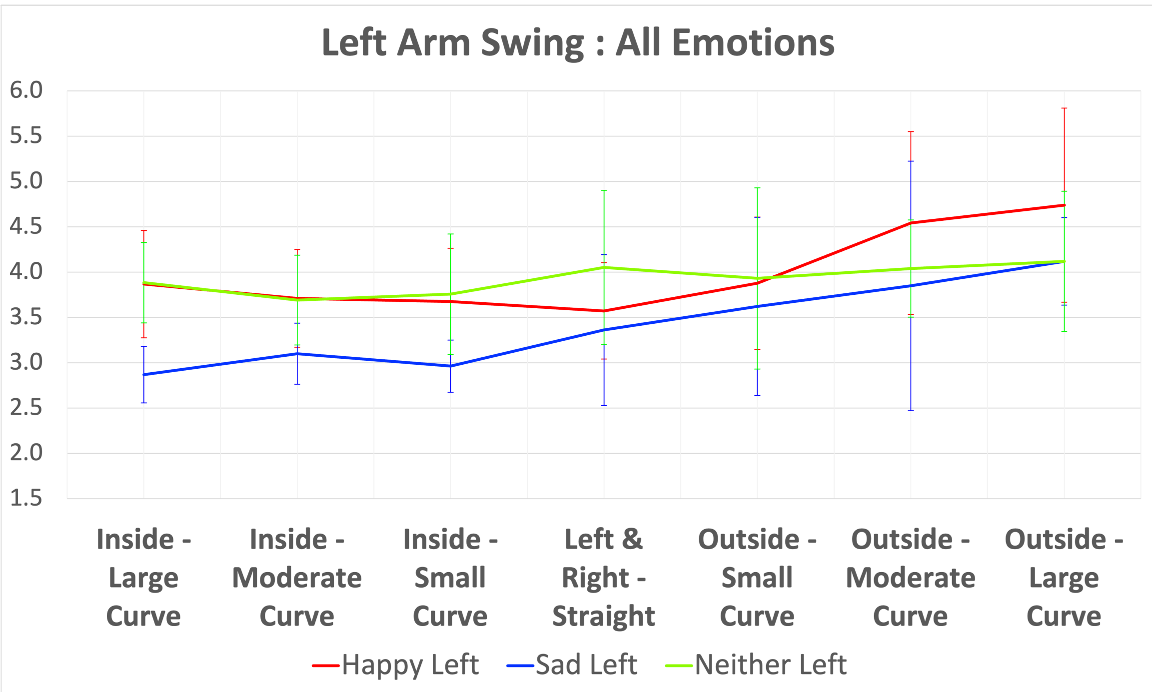

Figure 9.1: Plot of Left Arm Swing in All Emotions for the Combined Dataset

This combined dataset also shows some more angles that are useful to be

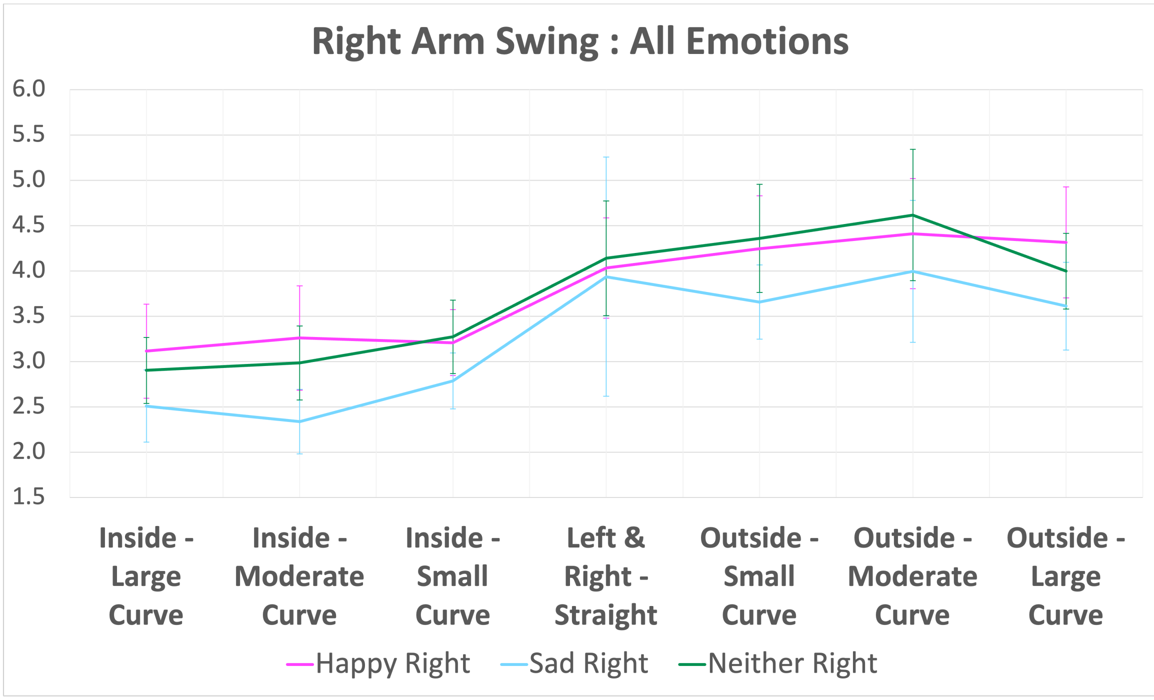

Figure 9.2: Plot of Right Arm Swing in All Emotions for the Combined Dataset

considered in addition to the left and right arm swing magnitudes (SD value of *BackRight-RightShoulderBack-RightUpperArmHigh* and SD value of *BackLeft-LeftShoulderBack-LeftUpperArmHigh*). As mentioned earlier, many differences in Table 9.1 are involving neither emotion, this study focuses only on happy and sad emotions which are opposite to each other. Happy and sad emotions also be the exact emotion unlike neither which means any other emotions except happy and sad. The angle names and the straightness groups which are significantly different between happy and sad emotion are as follows.

- -35° to -25°: SD of BackTop-RightShoulderBack-RightUpperArmHigh
- -25° to -15°: SD of BackTop-RightShoulderBack-RightUpperArmHigh
- -15° to -5°: Mean of BackTop-RightShoulderBack-RightUpperArmHigh and SD of BackLeft-BackTop-HeadTop

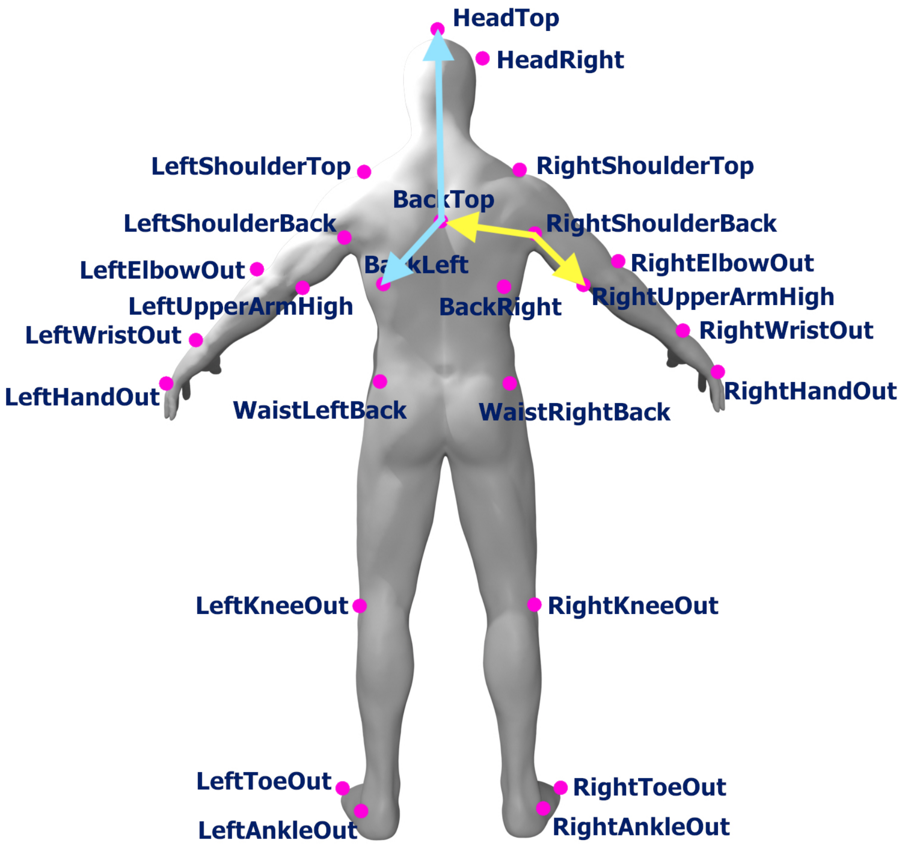

Figure 9.3: Illustration of Two Additional Angles which are Significantly Different between Happy and Sad

These angles are illustrated on the human model image in Figure 9.3. In this figure, the *BackTop-RightShoulderBack-RightUpperArmHigh* also represent the arm swing of subjects. The SD value shows the magnitude of arm swing in an entire walk of that straightness group, while the mean value represents the posture of the arm. In this case, right arm posture is different in happy and sad emotion. Another angle is *BackLeft-BackTop-HeadTop*. It can be interpreted as the head tilting angle, therefore, SD value of this angle is the magnitude of head tilting angle i.e., subjects tilt their head more in one emotion compared to another emotion.

9.2 Multi-Factor Analysis of Variance

9.2.1 Methodology

Multi-factor analysis of variance (ANOVA) was performed with the same method as used in the first dataset. In the combined dataset, multi-factor ANOVA was also performed on the same angles as done in the first dataset including SD value of *BackLeft-LeftShoulderBack-LeftUpperArmHigh*, and SD value of *BackRight-RightShoulderBack-RightUpperArmHigh* which are the left and right arm swing magnitudes. All other settings are similar to the experiment on the first dataset. Furthermore, because the combined dataset has more female subjects (51 male and 21 female) than the first dataset (41 male and 8 female), gender factor are also analyzed. The factors used in multi-factor ANOVA are as follows.

- Reported Emotion
- Curvature
- Angle Side
- Gender
- Reported Emotion × Curvature
- Reported Emotion × Angle Side
- Curvature × Angle Side
- Reported Emotion × Gender

- Curvature × Gender
- Angle Side × Gender

Additionally, in the second dataset that contains 23 subjects, more information about subjects was collected including dominant hand, dominant foot, and dominant brain side. This information is available for the second dataset only, hence, the following factors were analyzed using multi-factor ANOVA on the second dataset, not the combined dataset.

- Gender
- Dominant Hand
- Dominant Foot
- Dominant Brain Side
- Gender × Dominant Hand
- Gender × Dominant Brain Side
- Dominant Hand × Dominant Brain Side

9.2.2 Results

Results of multi-factor ANOVA are shown in Table 9.3 and Table 9.4 for the combined dataset and the second dataset respectively. In the combined dataset results, the factors which have significant effects on the arm swing magnitudes are *Reported Emotion, Curvature* and *Gender*. Moreover, these factors have interaction effects with each other including *Curvature* × *Angle Side, Reported Emotion* × *Gender, Curvature* × *Gender*, and *Angle Side* × *Gender* as shown in Table 9.3. For the second dataset analysis results using multi-factor ANOVA shown in Table 9.4, the factors which have significant effects with arm swing magnitudes are *Gender* and *Dominant Brain Side.* Also, there is an interaction effect between *Gender* and *Dominant Hand Side* factor.

Table 9.3: Results of Multi-Factor ANOVA for Combined Dataset

Factor	**Degree of Freedom**	**F-Value**	**P-Value**
Reported Emotion	2	11.8729	**0.0000**
Curvature	6	8.2373	**0.0000**
Angle Side	1	0.6141	0.4334
Gender	1	9.4269	**0.0022**
Reported Emotion × Curvature	12	0.3272	0.9846
Reported Emotion × Angle Side	2	0.1529	0.8582
Curvature × Angle Side	6	2.1078	**0.0495**
Reported Emotion × Gender	2	5.5106	**0.0041**
Curvature × Gender	6	2.4185	**0.0248**
Angle Side × Gender	1	4.2970	**0.0383**

Table 9.4: Results of Multi-Factor ANOVA for the Second Dataset

Factor	**Degree of Freedom**	**F-Value**	**P-Value**
Gender	1	24.5341	**0.0000**
Dominant Hand	2	0.6970	0.4984
Dominant Foot	1	0.0536	0.8169
Dominant Brain Side	3	8.8768	**0.0000**
Gender × Dominant Hand	2	5.8434	**0.0030**
Gender × Dominant Brain Side	1	3.4116	0.0652
Dominant Hand × Dominant Brain Side	3	2.2853	0.0776

From the results of the combined dataset in Table 9.3, Tukey test were conducted with these factors including *Reported Emotion* and *Gender* as these factors significantly affect arm swing magnitudes so it is important to find which pairs have significantly different arm swing magnitudes. The results of Tukey test for these two factors are shown in Table 9.5 and Table 9.6 respectively.

These tables show that arm swing magnitudes in *Happy vs Sad*, and *Neither vs Sad* are significantly different. Therefore, arm swing magnitudes can be used for distinguishing between different emotions. Besides, male and female subjects have significantly different arm swing magnitudes regardless of emotions.

Table 9.5: Significantly Different Pairs from Tukey Test on Reported Emotion of the Combined Dataset

Significant Pair	**P-Value from Tukey Test**
Happy vs Sad	0.0001
Neither vs Sad	0.0001

Table 9.6: Significantly Different Pairs from Tukey Test on Gender of the Combined Dataset

Significant Pair	**P-Value from Tukey Test**
Female vs Male	0.0049

For the second dataset multi-factor ANOVA test results in Table 9.4, Tukey test was performed on *Gender* factor. The result is shown in Table 9.7. Arm swing magnitudes are also significantly affected by subjects' gender. This result confirms that male and female subjects have different arm swings while walking.

Table 9.7: Significantly Different Pairs from Tukey test on Gender of the Second Dataset

Significant Pair	**P-Value from Tukey Test**
Female vs Male	0.0005

Chapter 10

Discussion

According to the results from all analyses, there are several issues should be considered as follows.

First of all, from one-way ANOVA results, human gait is obviously affected by the Reported Emotion from a self-reported questionnaire, more than by the Expected Emotion which is the annotated emotion from the videos used for emotion induction.

When comparing between Expected Emotion, all participants watched the same video for each Expected Emotion i.e., neutral, positive and negative video. The visual patterns, dialogues, sounds and musical rhythms are identical in each video. Therefore, the results suggest that the gait differences found in statistical analyses are not based on the raw video or audio stimuli, but on the reported emotions of subjects which were induced by these emotional videos.

According to one-way ANOVA results of Reported Emotion, several body part movements behaviors are affected by human emotion. For example, the mean values of angles related to the head and shoulders of subjects, and the standard deviation values of angles including movement magnitudes related to the chest, waist and arms of subjects. The left arm swing magnitude is significantly different in different reported emotions regardless of walking curvatures. However, difference in emotions among all curvatures only affected the left arm swing magnitude significantly but emotional difference does not significantly affect right arm swing magnitude. Since the participants in this study did not walk in a straight walking path but they walked circularly in different curvatures, it is possible that this phenomenon occurred due to the walking curvatures of the subjects.

From these results, arm swing magnitude in different walking curvatures were investigated. The plots of arm swing magnitudes shown in Figure 6.2 and Figure 6.3 show that the arm swing magnitude is smaller for the inside arm compared to the outside arm regardless of reported emotions or the arm sides. From the results of one-way ANOVA, this study focused on arm swing magnitude for Reported Emotion only in the remaining analyses. This study found that arm swings of humans can reveal their emotions better than other body parts. In addition, multi-factor ANOVA on arm swing magnitudes was used for investigation of walking curvatures and arm sides effects.

From the results of multi-factor ANOVA, many issues should be considered. For the main effects, this study shows that the Reported Emotion and Curvature have significant effects on arm swing magnitudes but the Angle Side (left or right arm) does not have a significant effect on arm swing magnitudes. Besides, two interaction effects related to the Angle Side were found including the Reported Emotion factor with Angle Side factor (F-Value=5.3906, P-Value=0.0047), and the Curvature factor with the Angle Side factor (F-Value=3.4769, P-Value=0.0020). In a related study by Kuhtz-Buschbeck et al. [22], they found that arm swing can be asymmetric for both left-handed and right-handed people. However, their study was conducted with straight walking path on the treadmill while this study was done using circular walking path. It is still possible that the arm swings of the left arm and right arm are asymmetric because of dominant hand of the participants while they walk in non-straight walking path. However, in the first dataset consisted of 49 subjects that was used for analyses, the dominant hand data were not collected. This issue can be tested using the second dataset. In addition, the Reported Emotion and walking curvature do not have interaction effects with each other in the first dataset.

From linear regression analysis, since the regression slopes of the left arm are much different for each emotion, but the regression slopes of the right arm are quite similar for all emotions, the arm swings in each emotion are affected differently for left and right arm. In other words, the differences of emotions have effects with the left and right arm swings in different ways. The results suggest the arm side must be considered in addition to the arm swing magnitude so that distinguishing between emotions is easier and more accurate.

In the first dataset, the numbers of male and female subjects are very different (41 males, 8 females). Also, the dominant hand information of each subject was not collected. Therefore, I decided to collect another dataset using the same setting and method. Besides, more information about subjects was collected including dominant hand, dominant foot, dominant brain side, and a question asking whether the subjects can walk naturally while watching videos on HoloLens 2. In the second dataset, there are 23 subjects including 13 female and 10 male participants. Since this dataset was collected using the similar method and setting which were used in the first dataset collection, this dataset was combined with the first dataset to make the entire dataset larger for analyses. In total, the combined dataset consists of 72 subjects including 51 male and 21 male subjects. Even though the numbers of male and female subjects are not equal, the ratio between male and female is much better than the first dataset. Also, analyzing the combined dataset which consists of more number of subjects should be better than analyzing two datasets separately.

The second dataset was collected to solve the following issues. First, the numbers of male subjects and female subjects in the first dataset are too much different. And the subjects in the first dataset were not asked for other information such as dominant hand, dominant foot etc. In this dataset, this information was collected for checking that the dominant side of body parts including hand, foot, and brain have effects with arm swing magnitude or not. As the previous dataset has asymmetric arm swing magnitudes, that is, magnitude of the left arm swing can reveal the emotions of subjects better than the right arm, and magnitude of left arm is always larger than right arm, collecting the second dataset that contains the information about dominant hand, foot, and brain side can be useful for further analyses.

Statistical analyses of the second dataset were perform by combining this dataset with the first dataset to make the dataset larger and more diverse between genders. One-way ANOVA and multi-factor ANOVA were performed using the similar method with the first dataset. One-way ANOVA results show that there are several body parts which are affected by the difference of emotions. However, using Expected Emotion does not have the good results since the emotions which subjects perceived are different from the emotions they were expected to feel. Therefore, the remaining analyses were performed using Reported Emotion only, and the emotions to consider are merely happy and sad because neither emotion is the emotion group that means the subjects did not feel happy and also did not feel sad so it should not be used for consideration.

The results from one-way ANOVA analysis which are significantly different between happy and sad emotions include the arm swing magnitudes of the left and right arm, and head tilting magnitudes of subjects. However, the body parts which have significantly different movements are not the same in all walking straightness groups unlike the first dataset. This can happened because of the combined dataset contains more number of subjects so the gait data are also more diverse. I analyzed the arm swing magnitudes of left and right arm although these angles are not significantly different in all walking straightness groups unlike the first dataset to verify whether the arm swing magnitudes have similar behavior with the first dataset. The results suggest that arm swing magnitudes of both left arm and right arm are different among different emotions and behave in the same trending with the first dataset. That is, when the subjects are happy, the arm swing magnitude is larger than when the subjects are sad for both arm sides. Also, from the plots of left and right arm swing magnitudes in each walking curvature level and when each arm is inside or outside of the circular walking path, the left arm is better to be used for observing subjects' emotions since the difference between emotions is larger in the left arm side. Additionally, when the arm is inside and the subjects walk in a highly curved pattern, arm swing magnitudes are also higher in the same manner as shown in the first dataset. Hence, the results from one-way

ANOVA and plots of arm swing magnitudes reveal that the behavior of arm swing magnitudes in different emotions, different walking curvature levels, and different sides are still the same even the number of subjects increases.

In multi-factor ANOVA analyses for the second dataset, some factors were tested using the combined dataset (72 subjects) while some factors were tested using the second dataset only (23 subjects). The reason is because the first dataset which consists of 49 subjects does not have the information about the dominant hand, dominant foot and dominant brain side. Consequently, the second dataset with 23 subjects was used for investigation of gender, dominant hand, dominant foot, and dominant brain side. The combined dataset with 72 subjects was used for checking other factors including Reported Emotion, curvature, angle side, and gender. In the combined dataset analysis, the factors which significantly affect with arm swing magnitudes are Reported Emotion (P-Value = 0.000, F-Value = 11.8729), Curvature (P-Value = 0.000, F-Value = 8.2373), and Gender (P-Value = 0.0022, F-Value = 9.4269). For the interaction between factors, Curvature has interaction with Angle Side (P-Value = 0.0495, F-Value = 2.1078), Reported Emotion has interaction with Gender (P-Value = 0.0041, F-Value = 5.5106), Curvature has interaction with Gender (P-Value = 0.0248, F-Value = 2.4185), and Angle Side has interaction with Gender (P-Value = 0.0383, F-Value = 4.2970). These results show that different emotions have significant effects with arm swing magnitudes, which agree with the first dataset analysis results. Curvature of walks are also significantly affect with arm swing magnitudes. As the ratio of male and female in the combined dataset is getting better, gender factor was also tested and the results show that male and female subjects have significantly different arm swing magnitudes.

The dominant body parts factors were tested using merely the second dataset. In this test, Gender (P-Value = 0.0000, F-Value = 24.5341) and Dominance Brain Side (P-Value = 0.0000, F-Value = 8.8768) have significant effects with subjects' arm swing magnitudes, and Gender also have interaction with Dominant Hand Side (P-Value = 0.0030, F-Value = 5.8434). Since this dataset has a very good ratio of male and female subjects (10 male and 13 female subjects), the results reveal that differences of arm swings are also related with gender. In other words, male and female subjects have significantly different arm swing magnitudes regardless of emotions and other factors. Subjects with different dominant brain sides also have significantly different arm swing magnitudes. Unfortunately, because the number of subjects are not many, so the dominant brain side in each group are less than 10 subjects i.e., 3 left-input/left-output, 7 left-input/right-output, 7 right-input/left-output and 6 right-input/right-output. The result suggests that brain side dominance also have effects with arm swing magnitudes but it may not very accurate as the number of subjects in each dominant brain side is less than ten subjects. But for the gender, as there are 13 female subjects and 10 male subjects, it can be concluded that subjects in different genders swing their arms differently.

Analyses results in this study reveal that the arm swing magnitudes are different in different emotions i.e., arm swing magnitude when subjects feel happy are larger than when subjects feel sad. My results agree with results from other related researches proposed by Halovic et al. [10], Michalak et al. [29] and Montepare et al. [30].

Halovic et al. [10] investigated the gait movements that can be used for distinguishing between emotions. Subjects walking in several emotions were shown to the observers using point-light display technique. They checked if the observers are aware of which gait cues are used to distinguish between emotions, and if the gait cues that the observers used for identification of emotions of walking subjects are actually shown in the walkers. All observers watched the same 409 videos recorded from 36 actors walking in several emotions including happiness, sadness, anger, fear and neutral at three intensity level i.e., low, moderate and high. There are approximately 80 to 100 videos for each emotion. Each observer were requested to watch the walkers expressing multiple emotions by point-light videos and rate the emotion classes as well as the intensity they perceived. A short question was used for asking about the observers' strategies to judge the emotions of the walkers. The most frequently used strategies for identifying each emotion are as follows. For happy emotion, gait is bouncy, walking speed is faster, and arm movement increases. However, for sad emotion, the walking speed is slower, arm movement decreases, and the head is down. In their study, they found that these cues are valid in all walking subjects, and the observers are explicitly aware of the cues they used for emotion identification. They also performed kinematic analysis to check if these cues actually happened and found that happy subjects walked faster with larger arm swing, but for sad subjects, the walking pace is slower and the arm swing is smaller due to the counterbalancing arm swing is not required much in slow walking unlike fast walking. Their findings are also agree with the studies by Michalak et al. [29] and Montepare et al. [30] which are the past studies about human gaits in different emotions. The study proposed by Halovic et al. [10] can be compared with my study although there are some differences i.e., subjects of their study walked in a straight walking path from one side of the room to another side of the room but subjects of my study walked in a circular walking pattern that includes several trajectories, and the walking subjects in their study are actors who performed the acted emotional expressions while walking whereas my study use unconscious emotional expressions of subjects while they watch emotion-inducing video. Their study proved that the arm swing and walking pace can be used to distinguish between happy and sad subjects, their finding about arm swing is consistent with my study. Unfortunately, as my study has smaller walking area and non-straight walking pattern, it is difficult to measure the walking speed in each emotion so the speed differences cannot be verified.

In the study proposed by Michalak et al. [29], they performed experiments to check the gait patterns which are related with dysphoric mood including sadness and depression. They compared the gait patterns of 14 patients with depression with 14 never-depressed participants in the first experiment. In the second experiment, they used music to induce negative and positive emotions of 23 participants. Each participant walked on a 7 meters length straight walking path for 10 times. For the first experiment, they compared 5 features i.e., speed, arm swing, lateral body sway, posture of the upper body, and vertical head movement. They found that there are significant differences between depressed and never-depressed participants for all features. That is, depressed participants have lower walking speed, reduced arm swing, larger lateral body sway, more slumped posture, and reduced vertical head movement. For the second experiment, two music were used for inducing emotions of subjects to be negative and positive. Gait features used for comparison are the same as the first experiment. This experiment show that all 5 features are significant between negative and positive mood condition i.e., sad participants walk slower, have reduced arm swing, have larger lateral body sway, have more slumped posture, and have reduced vertical head movement. Both experiments reveal that these 5 features can be used for discrimination between positive mood or never-depressed participants and negative mood or depressed participants. In comparison to my study, their study found more numbers of significantly different gait features between negative and positive emotions. This could be occurred because of the walking pattern and walking area size. As my study has circular walking path and much smaller walking area compared to their study which has straight and long walking path, differences of body movements in positive and negative emotion can be observed easier and clearer in their study. In summary, there is one common gait feature that is significantly different between emotions in my study and their study, that is, the arm swing of subjects.

Montepare et al. [30] conducted another study that should be considered. Ten observers were asked to observing five subjects expressing four emotions including sadness, happiness, anger, and pride. Observers identified the emotion of walking subjects by their gait characteristics. Each walker was requested to walk while imagining about the assigned situations related with these four emotions. The walking paths are straight toward, away, and across with the camera. Observers watched the recorded videos and judge the emotion of the walkers using the following criteria; short stride or long stride, no arm swing or much arm swing, light-footed or heavy-footed, and slouch or stand straight. Their experiments found that gaits of angry emotion are more heavy-footed than other emotions, and gaits of sad emotion have less arm swing than other emotions. Gaits of proud and angry emotions have longer stride length than other emotions, and happy emotion gaits has faster pace than other emotions. Results of this study also support my findings. That is, in sad emotion, the arm swing is less than other emotions. As my study compare between happy and sad emotion, their results are consistent with my results. However, for the walking speed or pace, their study also found the differences of walking speed between emotions while my study cannot test for the speed differences since the walking area is smaller and the walking path is not straight.

From the aforementioned researches, despite the walking directions and emotion induction methods of my study and these related studies are different, there is a similar gait feature that can be used for distinguishing between happy and sad walks i.e., the arm swing of subjects in happy walks are larger than sad walks regardless of walking directions or emotion induction methods.

The results of this study also show that the left arm swing is not symmetry with the right arm swing regardless of emotions, as well as left arm swing is larger and more obviously expresses the emotions of subjects. These results agree with other studies about left and right arm swing symmetry proposed by Killeen et al. [19] and Kuhtz-Buschbeck et al. [22]. That is, left arm swing is larger than right arm swing in healthy human, and it is not related with dominant hand of subjects.

Kuhtz-Buschbeck et al. [22] investigated the arm swing symmetry of 16 participants including 8 left-handed and 8 right-handed subjects when the subjects are walking on a treadmill. The objective of this study is to check whether the arm swing movement while walking is related with subject's dominant hand. There are 6 experimental conditions for each subject i.e., 4 forward walking trials, 1 backward walking trial, and 1 forward running trial. From the previous studies, there is a suggestion that the dominant hand side has less arm swing than the non-dominant hand side, however, their study found that this suggestion is not true. They also found that increased velocity results in increased amplitude of arm swing but when the subjects switch from walking to running, the amplitude of arm swing become smaller. And when the subjects walk backward, the arm swing decreased compare to forward walking at the same speed. For symmetry issue, they found that the arm swing is often asymmetry within subjects. There are 47 from 96 trials that have significantly different arm swing between each arm side. Ten subjects from 16 subjects have consistent asymmetry in different modes (forward/backward) and velocities of walking. Additionally, the dominant hand side has larger arm swing in 22 trial and the non-dominant hand side has larger arm swing in 25 trials which are very similar numbers. This means that the dominant hand side or handedness is not related with arm swing asymmetry. Particularly, they found that the left arm has larger arm swing than the right arm regardless of the dominant hand side. From their study, the results agree with the findings in my study that the arm swing on the left side is larger than arm swing on the right side, and is it common that the left and right arm swing asymmetric occurred in healthy subjects' gaits. In my study, the subjects walk in circular pattern which is a non-straight walking path while this study let their subjects walk on the treadmill which have unlimited walking length, the asymmetry of arm swing commonly occurred in both studies. These results suggest that asymmetry of left and right arm swings occurred regardless of walking pattern (straight/non-straight) and walking area size. Their study also shows that the dominant hand is not related with the arm swing which agree with my analysis results.

In a more recent study by Killeen et al. [19], asymmetric arm swing on overground walking was inspected. There are 334 subjects participated in their study. They performed experiments with 3 conditions of walking including normal walking, fast walking, and dual-task walking. In dual-task walking, serial subtraction task which is a cognitive task was performed by each subject during walking. Each subject was requested to walk back and forth in a hallway that has 20 meters length for one minute in each trial. For the normal walking task, subjects were asked to walk at their comfortable speed. For the fast walking task, subjects were asked to walk as fast as possible but not running and not making themselves injured. In dual-task walking, subjects were asked to walk at the same fast speed and perform a serial subtraction task by subtracting the number from 408 by 7 for the entire walking trial. Both walking task and cognitive task were performed equally without any task prioritized over another task. In their dataset, there are 255 strong right-handed subjects, 49 mixed right-handed subjects, 4 mixed-handed subjects, 23 mixed left-handed subjects, and 3 strong left-handed subjects. Their study found that 257 subjects which is the majority of subjects have larger arm swing on the left arm side.

Furthermore, 250 subjects have the same asymmetry arm side among all walking conditions. For the entire dataset, the average of left arm swing is larger than right arm swing. In dual-task walking condition, subjects who have larger arm swing on the left side responded to cognitive task more than subjects who have larger arm swing on the right side. In other words, if the subjects have larger left arm swing, the difference between left arm swing and right arm swing reduced when they performed dual-task walking. But if the subjects have larger right arm swing, the differences between left and right arm swings remained the same in all conditions. They also found that the dominant hand or handedness is not related with the arm swing asymmetry. Additionally, the walking speed significantly reduced when the subjects performed cognitive task during walking. This means that the cognitive task also affected with walking speed. In summary, their study reveals that the arm swing is asymmetric, and left arm swing is larger than right arm swing in overground walking regardless of walking conditions. This finding supports the results of my study that the arm swing is not symmetry and the left arm swing is larger than the right arm swing. This phenomenon is normal in healthy subjects. Moreover, their findings show that the dominant hand is not related with the asymmetry of arm swing which also agree with my results. Lastly, when subjects performed cognitive task, the difference between left and right arm swing can be reduced for the subjects who have larger left arm swing. In comparison to my study, walking while watching an emotion-inducing video can be considered as a cognitive task since the subjects have to pay attention to the contents of the video. This reason can explain why the difference of left and right arm swing in my study is not so large. For the walking pattern and walking space, this study shows that the long straight walking direction reveals large difference between left and right arm swing while my study used the circular walking pattern with smaller walking area size, hence, the asymmetry of left and right arm swing is not very large as found in their study.

From the studies proposed by Killeen et al. [19] and Kuhtz-Buschbeck et al. [22], it is normal that the arm swing for left arm and right arm are not symmetry in all walking conditions even though the walking direction and walking area size are different. These studies confirmed that the dominant hand of subjects are not related with subjects' arm swings. However, walking while performing cognitive task can make the asymmetry between both arms smaller but the asymmetry still exist in all situations.

Besides, emotions can be revealed unconsciously when the subjects are walking circularly. Walking in non-straight walking direction i.e., curved walk or turning can make the walking style of subjects to be unbalanced according to how the center of gravity is placed while walking[1]. Therefore, subjects tried to maintain the balance of walking so they unconsciously exert force in their walking postures, but the degree of force is unconsciously changed by emotions. It is possible that these unconscious force levels are affected by emotions of subjects easily. Therefore, when the body is in balance, the intensity of the emotion may differ unconsciously depending on the emotion of happiness or sadness.

Turcato et al. [43] examined human gait when walking in a circle. Their

[1] https://www.yamakei-online.com/yama-ya/detail.php?id=910

study is very useful to my study as they tested using the subjects who walked in clockwise and counter-clockwise direction which are similar to mine. They investigated the differences of gaits between linear and curved walking, and the distribution of force between both feet during curved walking. Their dataset consists of 26 participants walking in 3 conditions i.e., straight walking, circular clockwise walking, and circular counter-clockwise walking. Gaits were recorded using Pedar-X insole which is the device for measuring the pressure distribution on each foot, together with the accelerometer attached to the trunk of subjects. The walking path was marked as a circle with 1.2 meter radius on the floor. For straight walking task, the pathway has 20 meters length. For curved walking tasks, subjects were asked to walk for 3 times in each direction (clockwise/counter-clockwise) to collect 20 meters length of walking trials. Their study found that the walking speed and cadence were significantly affected by the walking trajectory between straight and curved walking. Speed and cadence are larger in straight walking compared to curved walking but the direction (clockwise and counter-clockwise) does not affect with these features in curved walking tasks. They discovered that the stance duration are similar for left and right foot in straight walking task. However, in curved walking tasks, the stance duration of the outside foot is shorter than the inside foot. For the trunk inclination issue, straight walking has very small inclination, while curved walking has larger inclination, that is, subject's trunk incline toward the center of the walking path. Their study can be used for explanation of some issues in my study. First, in my study, each subject can walk freely in the recording area without the path guidance on the floor while their study requested the subjects to walk on the marked line on the floor. Second, my study allows the subjects to switch the walking direction at anytime while their study let the subjects walk in clockwise and counter-clockwise direction separately. From their findings, the results suggest that subject's gait is affected by the walking trajectory between straight and curved walking. However, in my study, the subjects are allowed to walk circularly without the path guidance so some subjects have many curved walking data (oval-shaped walking subjects) whereas some subjects have few curved walking data and many straight walking data (rounded-rectangle walking subjects). For circular walking trajectory, this study is quite similar to my study as the size of the circle is fixed at 1.2 meters radius. In my study, the size of the circle or the oval is determined by each subject but the maximum circle size is limited by the entire walking area size (2.90 by 3.64 meters). Therefore, the walking area of the curved walking condition is not much different between my work and their work. This means that the gait characteristics they found in curved walking should be found in my study too. Unfortunately, the straight walking path in their work has 20 meters length, so it is much longer than my work which is limited by the walking area size as mentioned earlier. To summarize, gait characteristics in curved walking and straight walking is different, especially the body inclination, the walking speed, and the foot movement (stance duration) for each foot side. Hence, in my opinion, the subjects have to put more effort to maintain the walking balance in curved walking than in straight walking condition. And the reason why the curved walking in my study reveals more obvious emotional difference is that the subjects unconsciously exert the force to maintain their balance in curved walking. This force can be unconsciously affected by emotional differences.

Blakemore et al. [5] performed experiments to study the motor force output in several tasks. Participants were induced using emotional images selected from International Affective Picture System (IAPS) and subliminal stimuli (action-related words). A total of 270 images including 90 pleasant, 90 unpleasant and 90 neutral images were shown to the subjects. Subliminal stimuli consisted of words related to 3 types of adjective including action, inaction, and neutral adjectives. Force-measuring device between subject's thumb and index finger was used for measuring the force that subjects exert in each condition. Subjects were requested to press on the force measurement device as hard as possible while keep looking at the center of the screen. The unpleasant, pleasant, or neutral emotional images were shown to the subjects, then, the word related with action, inaction, or neutral meaning was shown. Finally, the subjects were asked to press the force measuring device. Therefore, each subject performed 9 conditions of experiment. They analyzed the force subjects used in each condition. There are 24 subjects participated in their study. In 9 conditions, they found significant interaction of emotional image and action-related words on motor force. When the subjects see the neutral image, maximum force was significantly lower when subjects also see the inaction word, compared to action and neutral words. This result shows that the inaction words make the motor output of subjects lower. However, when using neutral word and action word with neutral images, the forces are not significantly different between each word. Next, when the subjects see the emotional arousing images, different results were found according to the images and the action-related words. For inaction words, maximum force were found when using the unpleasant images while pleasant and neutral images make the force significantly lower. For action words, maximum forces were reduced in pleasant images conditions in comparison to neutral images and unpleasant images. In summary, these results reveal that the force output reduced in positive emotion, regardless of action or inaction words when comparing to neutral words. In addition, negative emotion makes the force output similar in all action-related words conditions. From their study, it could be summarize that the force subjects exert when feeling different emotions are also different. This means that emotion induction makes the subjects change the level of motor force and they did not aware that the force they used are lower or higher. From these results, their study is very meaningful for my study. As my study has an assumption that humans change their body movement or force they exert in each body part when they feel different emotions, the study proposed by Blakemore et al. [5] supports my assumption that the subjects unconsciously change their body movements when their emotion change.

Humans use nonverbal communication to transmit messages to other people. These messages can be expressed using many platform such as eye contacts, facial expressions, gestures, postures, or body languages. Several expressions can be shown both intentionally and unintentionally. The unintentional nonverbal expressions can be considered as human behaviors which are changed unconsciously and unintentionally in different situations. Sayler [37] mentioned about this point in their book interestingly. Gestures can be expressed unintentionally when the subjects unconsciously react to some emotions they feel. In other words, unintentional gestures are reactions from emotions or the desire for physical comfort of the body. This behavior can be called *fidgets*. Some well-known fidgets includes touching the face and neck, vibrating the leg while seated, and clicking on the pen. Many researches found that unintentional body expressions are related with human emotions. For instance, the study proposed by Hussain et al. [11] proposed a mental state prediction system by analyzing human gestures. They examined the unintended gestures that the subjects perform while taking an analytical test. An analytical question paper was given to each subject and the subject was requested to solve the question within a limited time. There are 20 subjects participated in this study. The unintended gestures were recorded when the subjects are solving analytical question. They found that there are unintended gestures occurred including the hand-touch-head and hand-touch-face movements. A system for prediction of subjects' mental states was developed. From their method, prediction of subjects' affective states yields 84% to 97% accuracy. Hence, they found that human body language or gesture is a nonverbal behavior that can reveal subjects' emotions which are expressed unintentionally, and these unconscious behaviors are very useful for developing an application for real-life situations.

A recent study by Liu et al. [28] studied about the nonverbal body gestures without using subjects' identity information. Their work focuses on the unintentional behaviors driven by inner feelings of subjects. Emotional states behind gestures were investigated and a recognition model was built. Their dataset contains the scenarios from videos of post-match press conferences available on the Internet. These videos show the professional athletes who were interviewed by reporters after they just finished a match. As the athletes have very little time to prepare, the responses to interviewing questions also express the unintentional and unconscious behaviors. Emotion states of the subjects were induced naturally by the results of the matches. In their study, they used two emotion categories i.e., positive state and negative state. There are 359 videos including 258 wins and 101 losses post-match press conference videos. Five major groups of gestures were examined in their study according to the location of body parts i.e., head, body, hand, body-hand, and head-hand. Each group contains more detailed body movements. Some examples of gestures in each group are moving torso, shaking shoulder for body group; turtle neck, head up for head group; scratching arms, crossing fingers, rubbing hands for hand group etc. Their study yields 60% best accuracy on recognition of emotions between emotions using their proposed dataset and technique. Although the recognition accuracy is not so high because of many limitations such as the very short timing of each gesture, their study is very useful as it reveals that human emotions are unconsciously expressed by human behaviors especially the body gestures. From these related studies, it is obvious that human behaviors especially gaits and gestures are related with subjects' feelings and they can be expressed unintentionally and unconsciously. These studies support our assumption that human behaviors including gaits and gestures can be expressed and changed unintentionally by subjects' inner feelings.

To sum up, by comparison between my study with other related studies, some points which need supporting reasons can be explained by other related works. In my study, the arm movements of subjects are smaller when subjects are walking in sad emotion comparing to happy emotion. Other related works proposed by Halovic et al. [10], Michalak et al. [29] and Montepare et al. [30] are consistent with my results, despite the walking patterns and directions, walking spaces, and emotion induction methods are different. Therefore, the arm movements or arm swings of subjects can be used to distinguish between happy and sad emotions. Secondly, my results show that the arm swings of left arm and right arms are not symmetry, and left arm swing shows subjects' emotional differences more obviously than the right arm swing. According to the studies about symmetric of arm swings proposed by Killeen et al. [19] and Kuhtz-Buschbeck et al. [22], their findings reveal that left and right arm swings of healthy subjects are normal to be asymmetric, and it is also normal that the left arm swing is larger than the right arm swing regardless of subjects' dominant hands or handedness. This phenomenon is normal although the walking directions, patterns, surfaces, and walking spaces are different. Besides, because my study uses a non-straight walking path for subjects to walk i.e., each subject walk circularly, it is also interesting to check whether the circular walking pattern is related with body balance and unconscious force that subjects exert while walking to maintain their balance. The study proposed by Turcato et al. [43] reveals that subjects have to use more effort to balance their bodies when walking circularly so subjects' gaits are affected by walking trajectories. Hence, these findings suggest that subjects have to put more effort by unconsciously exerting some forces to maintain their balance while walking in a non-straight walking path. Furthermore, it is still ambiguous that the forces that subjects' used for maintaining balance when walking can be unconsciously changed due to emotional differences or not. A study by Blakemore et al. [5] supports this assumption. They found that the hand forces that subjects exert to force-measuring device are different when the emotional states of subjects change, definitely, subjects are not aware about these changes. Additionally, several behaviors which are nonverbal communication methods of humans can be expressed unintentionally or unconsciously when subjects react to some emotional stimuli or from their physical desires as mentioned by Sayler [37]. The works proposed by Hussain et al. [11] and Liu et al. [28] also reveal that human gestures are unconsciously changed or expressed depending on the affective states of subjects. Therefore, these related works clarify the ambiguous issues in my study. By walking in a non-straight path, subjects unconsciously put some forces to maintain their balance, and these forces can be changed according to subjects' emotions, as well as other forces such as hand pressing force which is changed without awareness of the subjects when subjects' emotions change. This means that human gaits while walking in a non-straight walking path, especially the left arm swing, can be used for identifying subjects' current emotions effectively.

In brief, the results of all statistical analyses can confirm these hypotheses. First, body part movements are different when the subjects are walking in different emotions. Therefore, human walking posture can reveal his or her emotions. Second, the body part movements, especially the arm swing, of the left and right sides while subjects are walking in a non-straight walking path are not symmetric. Hence, one side can reveal subject's emotion better than another side. These asymmetric movement of human body in each side is not related with dominant hand and dominant foot.

In emotion induction perspective, using HoloLens 2 to display emotion-inducing videos during walking is more effective and consistent than using conventional displays to show the videos before walking. Unfortunately, from the subjects' comments in the questionnaire, several subjects feel that they cannot walk normally when they watched the video on HoloLens 2 while walking. Some subjects have motion sickness; some subjects feel tired; some subjects feel bored; some subjects feel sleepy; some subjects feel that concentrating on both walking and watching videos is difficult; and some subjects concern that they will go out from the walking area during walking. Oppositely, several subjects feel that it is easy to walk; some also feel that they can concentrate on the video and do not need to concern about walking posture; and some subjects say they can see the room environment while walking as the HoloLens 2 is transparent. Hence, the main limitations of this study are because of the walking environment and video induction method that is a novel method which has never been used before. These can be solved in the future by the following ideas. First, the walking space should be larger to make the subjects walk more natural. Second, the videos for emotion induction should not be too long and should be easy to understand to avoid the subjects to feel tired, bored or sleepy. Third, the subjects should have more time to practice using HoloLens 2 before perform the gait data collection to make them feel familiar with watching contents on smart glasses while walking. Finally, to avoid motion sickness, using some animated agents to interact with the subjects to induce their emotions can be a better idea than using the entire movie. In summary, using real-time emotion induction while walking is a good start point of novel emotion induction methods. Even there are still some flaws and limitations, it is worth to investigate and conduct experiments using HoloLens 2 or other smart glasses for emotion induction.

There are several useful findings from this study for the emotion recognition research field. Humans gaits can reveal current emotions of subjects while walking although in a non-straight walking path. The arm swing magnitudes can show the differences of human emotions effectively and if the walking curvature data as well as the arm side data are known, it will be much easier to distinguish between emotions. The results of this study are expected to be useful for developing an accurate emotion recognition system from gaits that can performs in a real-world environment where the subjects are walking in a crowded environment without requiring high-quality cameras or specific equipment and without subjects' awareness. Since humans emotions can be detected by subjects' arm swing magnitudes, there is no need to use complex equipment to capture the gait data. Any camera such as CCTV camera can be used together with pose-estimation software to calculate the essential features for emotion prediction.

Chapter 11

Conclusion

The differences of body part movements, while subjects are walking in a non-straight path and watching emotion-inducing videos using Microsoft HoloLens 2, were investigated in this study. Due to the non-straight walking path used in this study, gait data for different curvatures can be obtained. OptiTrack motion-capturing system with 37 markers was used for recording human gaits. Emotional videos were used for emotion induction by displaying the videos on HoloLens 2 while subjects are walking. However, not all subjects felt the same emotion as expected. Hence, it is essential to ask the subjects about their feelings after finishing emotion induction. Gait features were calculated from 24 angles that show the movements of body parts while subjects are walking. Walking straightness and the curvature level of walking were computed as well as the inside-outside status of body side. According to the results of statistical analyses on gait data including one-way ANOVA, multi-factor ANOVA, and linear regression analysis, the magnitudes of arm swing are larger when the subjects are walking and feeling happy than when the subjects are walking and feeling sad. Besides, if the walking path is not straight, observing the body movements on one side will be easier for prediction of emotions than another side. This study found that the left arm swing can reveal the current emotion of subjects better than the right arm swing, especially when the left arm is outside of circular walking path and the subjects are walking with high curvature trajectories. From all analyses, the results suggest that body part movements while walking are different under different emotions. Therefore, emotions of humans can be detected from their gaits. Particularly, arm swing magnitude can reveal current emotions of subjects better than any other parts of the body.

This study can be considered as an investigation that shows the differences of human gaits when walking in different emotions. Although there are some limitations such as the numbers of emotions are limited to only three types including happy, sad and neither, this study shows that emotion induction using smart glasses to show the videos for real-time emotion induction is effective and consistent. This emotion induction method is a novel method that no one has ever used before. Obviously, walking when feeling happy and walking when feeling sad have significantly different arm swings when the subjects walk in both straight and non-straight walking paths. Also, distinguishing between emotions is easier when the arm side information are known. These findings have the potential to be used for developing an automatic emotion recognition system that works with any walking trajectories. Gait data in a real-world scenario can be captured from far away without subject's awareness by standard video camera with a pose-estimation software e.g., OpenPose, or by markerless motion capturing devices such as Microsoft Kinect or Intel RealSense.

List of Publications

International Conferences and Workshop

- Nitchan Jianwattanapaisarn, Kaoru Sumi, Akira Utsumi, Nirattaya Khamsemanan and Cholwich Nattee: Analysis of Non-Straight Walking Human Gaits in Different Emotions, Workshop on Computation: Theory and Practice, Nov. 2021.
- Nitchan Jianwattanapaisarn, Kaoru Sumi, Akira Utsumi: Emotion Recognition from Non-Straight Walking Gaits Induced by Emotional Videos, 3rd Momentary Emotion Elicitation & Capture (MEEC), Hybrid Workshop at ACII 2022, In Press.

International Journal

- Nitchan Jianwattanapaisarn and Kaoru Sumi: Investigation of Real-time Emotional Data Collection of Human Gaits Using Smart Glasses, Journal of Robotics, Networking and Artificial Life, Volume 9, Issue 2, pp. 159-170 (2022).
- Nitchan Jianwattanapaisarn, Kaoru Sumi, Akira Utsumi, Nirattaya Khamsemanan and Cholwich Nattee: Emotional Characteristic Analysis of Human Gait while Real-Time Movie Viewing, Frontiers in Artificial Intelligence (2022), Under Review.

Book Chapter

- Nitchan Jianwattanapaisarn and Kaoru Sumi: Methods for Real-time Emotional Data Collection on Human Gait, Intelligent Video Surveillance - New Perspectives, IntechOpen (2022), In Press.

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Appendix

The full results of one-way ANOVA for mean and SD of all 24 angles in each straightness group are shown as follows.

- Expected Emotion factor with the first dataset
- Reported Emotion factor with the first dataset
- Expected Emotion factor with combination of both datasets
- Reported Emotion factor with combination of both datasets

Table 1: Results of One-Way ANOVA for Mean and SD of Each Angle in Each Straightness Group for the First Dataset (Factor: Expected Emotion)

Angle Name	**Type**	**Degrees of Freedom**	**-35° to -25°**		**-25° to -15°**		**-15° to -5°**		**-5° to 5°**		**5° to 15°**		**15° to 25°**		**25° to 35°**	
			F-Value	**P-Value**	**F-Value**	**P-Value**	**F-Value**	**P-Value**	**F-Value**	**P-Value**	**F-Value**	**P-Value**	**F-Value**	**P-Value**	**F-Value**	**P-Value**
LeftAnkleOut-LeftKneeOut-WaistLeftFront	Mean	2	0.6987	0.5019	0.0630	0.9390	0.5669	0.5691	0.4628	0.6305	0.7150	0.4911	0.4281	0.6527	0.0274	0.9730
	SD	2	1.4229	0.2503	0.7884	0.4596	0.2048	0.8151	1.1753	0.3119	0.7593	0.4701	0.6692	0.5140	0.0619	0.9400
RightAnkleOut-RightKneeOut-WaistRightFront	Mean	2	0.0400	0.9608	0.2012	0.8183	0.2380	0.7887	0.2609	0.7707	0.1876	0.8292	0.0528	0.9486	0.1438	0.8662
	SD	2	0.3288	0.7213	0.5030	0.6074	0.5824	0.5604	0.4580	0.6335	0.3936	0.6754	0.2081	0.8124	0.3454	0.7086
LeftShin-LeftKneeOut-LeftThigh	Mean	2	0.3689	0.6933	0.0266	0.9738	0.0402	0.9606	0.1281	0.8799	0.0466	0.9545	0.0124	0.9877	0.0645	0.9376
	SD	2	0.9747	0.3841	0.8820	0.4196	0.0043	0.9957	0.1084	0.8973	0.2077	0.8127	0.1842	0.8320	0.1457	0.8645
RightShin-RightKneeOut-RightThigh	Mean	2	0.0961	0.9086	0.5365	0.5878	0.1823	0.8336	0.0654	0.9367	0.2214	0.8017	0.0934	0.9109	0.0191	0.9811
	SD	2	0.2366	0.7901	0.7163	0.4930	0.2288	0.7959	0.4617	0.6312	0.2421	0.7854	0.0345	0.9661	0.2518	0.7778
LeftKneeOut-LeftThigh-WaistLeftFront	Mean	2	0.1162	0.8905	0.0672	0.9351	0.3171	0.7290	0.1885	0.8285	0.1517	0.8594	0.1323	0.8762	0.0731	0.9296
	SD	2	0.3972	0.6742	0.5685	0.5696	0.1123	0.8939	0.1519	0.8592	0.0871	0.9167	0.2593	0.7720	0.1770	0.8380
RightKneeOut-RightThigh-WaistRightFront	Mean	2	0.0272	0.9732	0.2478	0.7814	0.3318	0.7184	0.0409	0.9599	0.0489	0.9523	0.0056	0.9944	0.0342	0.9664
	SD	2	0.0176	0.9826	0.4165	0.6614	0.0561	0.9455	0.5370	0.5857	0.1358	0.8732	0.0396	0.9612	0.2599	0.7716
LeftThigh-WaistLeftFront-Chest	Mean	2	0.0575	0.9442	0.2484	0.7809	0.0225	0.9777	0.0505	0.9508	0.0442	0.9568	0.0635	0.9385	0.0796	0.9235
	SD	2	0.7141	0.4944	0.7336	0.4847	0.0286	0.9719	0.0578	0.9439	0.5089	0.6023	0.4121	0.6632	0.2039	0.8158
RightThigh-WaistRightFront-Chest	Mean	2	0.0019	0.9981	0.0953	0.9093	0.3291	0.7204	0.0359	0.9647	0.0404	0.9605	0.0015	0.9985	0.0004	0.9996
	SD	2	0.2227	0.8011	0.3880	0.6802	0.6301	0.5346	0.2490	0.7799	0.3234	0.7243	0.5774	0.5629	0.7637	0.4682
WaistLeftFront-Chest-LeftShoulderTop	Mean	2	0.0673	0.9350	0.1955	0.8230	0.0322	0.9684	0.0839	0.9196	0.0410	0.9598	0.0633	0.9387	0.0654	0.9367
	SD	2	0.4684	0.6286	1.2575	0.2923	0.4890	0.6147	0.4218	0.6567	0.6656	0.5157	0.6061	0.5471	0.8730	0.4203
WaistRightFront-Chest-RightShoulderTop	Mean	2	0.0326	0.9679	0.0055	0.9945	0.1610	0.8515	0.0369	0.9638	0.0259	0.9744	0.1441	0.8660	0.1333	0.8753
	SD	2	0.9598	0.3897	1.2461	0.2955	0.3207	0.7264	0.1894	0.8277	0.2634	0.7688	0.1474	0.8631	0.4252	0.6546
LeftKneeOut-WaistLeftBack-BackLeft	Mean	2	0.1133	0.8931	0.0771	0.9259	0.4082	0.6660	0.3419	0.7110	0.0088	0.9913	0.0080	0.9920	0.0221	0.9782
	SD	2	0.6723	0.5149	0.7105	0.4958	0.1871	0.8296	0.1079	0.8978	0.2782	0.7576	0.1335	0.8752	0.0226	0.9776
RightKneeOut-WaistRightBack-BackRight	Mean	2	0.0326	0.9680	1.0470	0.3577	0.0834	0.9200	0.5913	0.5550	1.0922	0.3385	0.5290	0.5906	0.3380	0.7139
	SD	2	0.4738	0.6253	0.3182	0.7287	0.8494	0.4307	1.9243	0.1500	1.9279	0.1496	1.1144	0.3314	0.2577	0.7732
WaistLeftBack-BackLeft-LeftShoulderBack	Mean	2	0.0055	0.9945	0.0524	0.9490	0.0588	0.9430	0.1206	0.8864	0.1133	0.8930	0.1484	0.8622	0.1787	0.8366
	SD	2	0.2455	0.7832	0.0746	0.9282	0.1165	0.8902	0.5529	0.5766	0.3701	0.6914	0.1270	0.8808	0.2624	0.7696
WaistRightBack-BackRight-RightShoulderBack	Mean	2	0.0164	0.9837	0.2105	0.8108	0.2754	0.7599	0.1907	0.8266	0.4627	0.6306	0.1733	0.8411	0.1627	0.8501
	SD	2	0.6988	0.5018	0.8341	0.4396	0.7722	0.4647	1.9541	0.1457	1.8371	0.1634	1.8335	0.1643	0.9480	0.3904
LeftShoulderBack-BackTop-HeadTop	Mean	2	0.1003	0.9048	0.0646	0.9375	0.0058	0.9942	0.0909	0.9131	0.1221	0.8851	0.0539	0.9475	0.0722	0.9304
	SD	2	0.5386	0.5868	0.1024	0.9028	0.6025	0.5494	1.8318	0.1641	1.9491	0.1465	2.0333	0.1353	2.4667	0.0891
RightShoulderBack-BackTop-HeadTop	Mean	2	0.2849	0.7533	0.3381	0.7146	0.1859	0.8307	0.7313	0.4832	0.4392	0.6455	0.3593	0.6989	0.3400	0.7125
	SD	2	0.3272	0.7224	0.0465	0.9546	1.6002	0.2069	2.3775	0.0967	1.5533	0.2154	1.8237	0.1658	3.6983	**0.0276**
BackLeft-BackTop-HeadTop	Mean	2	0.1957	0.8229	0.1944	0.8239	0.2522	0.7776	0.3959	0.6739	0.4448	0.6419	0.2402	0.7869	0.2648	0.7678
	SD	2	0.9232	0.4037	0.2502	0.7795	0.1858	0.8307	1.7377	0.1799	1.1061	0.3339	1.1375	0.3240	1.0224	0.3628
BackRight-BackTop-HeadTop	Mean	2	0.1226	0.8849	0.1470	0.8637	0.1691	0.8447	0.0811	0.9221	0.3629	0.6964	0.2208	0.8022	0.3136	0.7314
	SD	2	1.2557	0.2934	0.1276	0.8805	0.6979	0.5000	1.3334	0.2670	1.4269	0.2438	1.9193	0.1511	1.3109	0.2734
BackLeft-LeftShoulderBack-LeftUpperArmHigh	Mean	2	1.0053	0.3730	0.7051	0.4984	0.6048	0.5482	0.0536	0.9478	0.0696	0.9328	0.1110	0.8951	0.0803	0.9229
	SD	2	0.8814	0.4203	1.2342	0.2989	0.7095	0.4943	0.8023	0.4505	0.6222	0.5384	0.8106	0.4470	1.5265	0.2215
BackRight-RightShoulderBack-RightUpperArmHigh	Mean	2	0.1877	0.8294	0.1031	0.9022	0.7849	0.4590	0.4870	0.6156	0.2734	0.7612	0.2687	0.7648	0.1749	0.8397
	SD	2	1.0834	0.3460	1.3641	0.2640	0.4045	0.6684	0.5204	0.5955	0.5944	0.5534	0.4766	0.6220	0.4526	0.6370
BackTop-LeftShoulderBack-LeftUpperArmHigh	Mean	2	0.8956	0.4146	0.8612	0.4282	0.2046	0.8153	0.2388	0.7879	0.1776	0.8375	0.1046	0.9007	0.1015	0.9036
	SD	2	0.4737	0.6254	0.4183	0.6602	0.1621	0.8506	1.0618	0.3487	1.5991	0.2060	1.4489	0.2389	0.4938	0.6115
BackTop-RightShoulderBack-RightUpperArmHigh	Mean	2	0.3612	0.6986	0.4943	0.6126	0.2053	0.8148	0.7697	0.4652	0.5401	0.5840	0.3806	0.6843	0.3361	0.7152
	SD	2	0.3637	0.6969	0.7683	0.4686	0.0051	0.9949	0.5426	0.5825	0.6985	0.4992	1.1292	0.3267	1.9275	0.1500
LeftUpperArmHigh-LeftElbowOut-LeftWristOut	Mean	2	1.4454	0.2450	0.6532	0.5243	0.8158	0.4452	0.5184	0.5967	0.4014	0.6702	0.4382	0.6462	0.3603	0.6982
	SD	2	0.2067	0.8139	0.3699	0.6925	0.5952	0.5533	0.6584	0.5194	0.8055	0.4491	1.0016	0.3703	1.0944	0.3380
RightUpperArmHigh-RightElbowOut-RightWristOut	Mean	2	0.2920	0.7480	0.5579	0.5756	0.1339	0.8748	0.1503	0.8606	0.0079	0.9922	0.7635	0.4683	1.0489	0.3535
	SD	2	0.5626	0.5731	1.2252	0.3015	0.8732	0.4208	0.9758	0.3796	1.1729	0.3127	0.9895	0.3747	0.5837	0.5594

Table 2: Results of One-Way ANOVA for Mean and SD of Each Angle in Each Straightness Group for the First Dataset (Factor: Reported Emotion)

Angle Name	Type	Degrees of Freedom	-35° to -25°		-25° to -15°		-15° to -5°		-5° to 5°		5° to 15°		15° to 25°		25° to 35°	
			F-Value	P-Value	F-Value	P-Value	F-Value	P-Value	F-Value	P-Value	F-Value	P-Value	F-Value	P-Value	F-Value	P-Value
LeftAnkleOut-LeftKneeOut-WaistLeftFront	Mean	2	0.4845	0.6188	0.4657	0.6301	0.4470	0.6408	0.4713	0.6252	0.1020	0.9031	0.0909	0.9131	0.7818	0.4599
	SD	2	0.6812	0.5105	1.3633	0.2642	0.1778	0.8373	0.4065	0.6668	0.8391	0.4344	2.5143	0.0851	0.8202	0.4428
RightAnkleOut-RightKneeOut-WaistRightFront	**Mean**	2	0.5185	0.5985	5.5611	**0.0063**	2.9376	0.0575	0.2956	0.7446	0.3023	0.7396	0.0331	0.9674	0.0279	0.9725
	SD	2	0.5383	0.5869	0.2925	0.7476	1.3475	0.2645	0.6572	0.5200	0.7174	0.4899	1.9441	0.1476	0.8614	0.4251
LeftShin-LeftKneeOut-LeftThigh	Mean	2	0.0484	0.9528	0.2797	0.7571	0.0162	0.9839	0.3218	0.7254	0.5134	0.5996	0.5020	0.6066	1.0129	0.3662
	SD	2	1.0287	0.3646	0.8801	0.4204	2.2178	0.1141	0.8895	0.4133	1.5201	0.2226	2.3493	0.0998	0.7299	0.4841
RightShin-RightKneeOut-RightThigh	Mean	2	0.0336	0.9670	0.3826	0.6838	0.2186	0.8041	0.4932	0.6118	0.3929	0.6759	0.4171	0.6599	0.8981	0.4100
	SD	2	2.0007	0.1455	1.9058	0.1582	1.3421	0.2659	0.2658	0.7670	0.2274	0.7970	0.6056	0.5474	1.7291	0.1818
LeftKneeOut-LeftThigh-WaistLeftFront	Mean	2	0.3220	0.7262	0.1940	0.8242	0.0450	0.9560	0.9174	0.4021	0.6264	0.5361	0.7198	0.4889	0.6020	0.5493
	SD	2	0.2257	0.7988	1.0393	0.3604	2.6192	0.0778	0.3334	0.7171	0.2672	0.7659	0.7239	0.4869	0.1148	0.8916
RightKneeOut-RightThigh-WaistRightFront	Mean	2	0.0146	0.9855	0.2310	0.7945	0.3152	0.7303	0.7140	0.4915	0.5416	0.5831	1.1918	0.3072	0.9561	0.3873
	SD	2	0.1855	0.8313	1.2099	0.3059	0.1851	0.8313	0.9210	0.4006	0.4243	0.6551	1.4454	0.2397	1.2993	0.2765
LeftThigh-WaistLeftFront-Chest	Mean	2	0.3876	0.6807	0.0256	0.9747	0.8356	0.4366	1.1208	0.3291	0.9014	0.4085	0.9257	0.3991	0.8437	0.4326
	SD	2	0.2137	0.8083	0.7045	0.4987	1.6209	0.2028	1.6481	0.1963	0.4574	0.6340	0.5656	0.5695	0.3365	0.7149
RightThigh-WaistRightFront-Chest	Mean	2	0.1644	0.8488	0.3378	0.7148	0.9859	0.3767	0.4663	0.6283	0.1492	0.8616	0.7130	0.4922	0.4879	0.6151
	SD	2	0.8236	0.4445	2.5884	0.0841	0.6103	0.5452	1.8801	0.1566	0.5680	0.5680	0.1314	0.8770	0.2727	0.7618
WaistLeftFront-Chest-LeftShoulderTop	Mean	2	0.9145	0.4071	0.8174	0.4468	1.3427	0.2658	1.6144	0.2029	1.8164	0.1667	1.1176	0.3304	1.1843	0.3095
	SD	2	2.1649	0.1250	3.5329	**0.0359**	0.6072	0.5469	0.5502	0.5781	1.0983	0.3365	0.9759	0.3798	1.9595	0.1454
WaistRightFront-Chest-RightShoulderTop	Mean	2	0.7710	0.4677	0.6719	0.5148	0.4229	0.6563	0.2794	0.7567	0.3841	0.6818	0.7168	0.4904	0.8103	0.4471
	SD	2	2.0888	0.1341	4.6688	**0.0133**	0.6010	0.5502	1.9995	0.1394	0.4906	0.6134	1.3305	0.2682	1.5063	0.2259
LeftKneeOut-WaistLeftBack-BackLeft	Mean	2	0.2721	0.7629	0.3625	0.6976	0.2912	0.7480	1.8402	0.1628	1.0133	0.3659	0.7293	0.4844	0.7647	0.4677
	SD	2	0.2765	0.7596	3.4477	**0.0387**	0.7650	0.4680	0.5142	0.5992	0.8033	0.4501	1.5869	0.2088	1.0004	0.3707
RightKneeOut-WaistRightBack-BackRight	Mean	2	1.1541	0.3233	0.8457	0.4347	1.3287	0.2695	1.9146	0.1514	1.6376	0.1984	1.5744	0.2113	1.0199	0.3637
	SD	2	0.1448	0.8655	1.0217	0.3666	0.4833	0.6182	0.0701	0.9323	0.0521	0.9493	0.1252	0.8825	0.1395	0.8699
WaistLeftBack-BackLeft-LeftShoulderBack	Mean	2	0.1492	0.8617	0.3764	0.6881	0.2840	0.7534	1.0613	0.3489	0.9299	0.3972	1.0790	0.3432	0.9948	0.3728
	SD	2	0.1619	0.8510	0.2335	0.7925	0.7214	0.4886	0.3195	0.7271	2.0702	0.1303	3.1031	0.0485	2.4005	0.0950
WaistRightBack-BackRight-RightShoulderBack	Mean	2	0.7306	0.4865	0.9563	0.3905	0.4072	0.6666	2.4226	0.0926	2.1401	0.1218	2.1141	0.1252	2.1851	0.1169
	SD	2	0.6572	0.5225	0.8903	0.4163	0.8087	0.4483	0.2036	0.8161	0.0944	0.9100	0.3177	0.7284	0.4623	0.6309
LeftShoulderBack-BackTop-HeadTop	Mean	2	1.1209	0.3337	0.9886	0.3785	2.1281	0.1244	1.4770	0.2320	1.6585	0.1944	2.4785	0.0881	2.5454	0.0826
	SD	2	0.1825	0.8338	0.0951	0.9094	0.6739	0.5120	0.3303	0.7193	0.0124	0.9877	0.6777	0.5097	0.7725	0.4641
RightShoulderBack-BackTop-HeadTop	**Mean**	2	1.3644	0.2645	1.7783	0.1783	1.8622	0.1606	3.5905	0.0303	3.1532	0.0460	3.8224	**0.0246**	3.6483	**0.0289**
	SD	2	0.0176	0.9825	0.1755	0.8395	0.3759	0.6877	0.1106	0.8954	0.0546	0.9469	1.2251	0.2973	1.3075	0.2743
BackLeft-BackTop-HeadTop	Mean	2	0.7225	0.4903	1.2970	0.2814	1.5026	0.2275	0.3595	0.6987	0.8208	0.4424	1.0128	0.3663	1.0605	0.3495
	SD	2	0.1865	0.8304	0.0673	0.9350	1.0389	0.3576	0.2770	0.7585	0.4246	0.6550	0.1453	0.8649	0.2800	0.7563
BackRight-BackTop-HeadTop	Mean	2	0.3262	0.7232	0.8130	0.4487	1.5697	0.2132	2.0942	0.1272	1.9272	0.1497	1.4560	0.2372	1.6514	0.1961
	SD	2	0.2449	0.7837	0.1288	0.8794	0.2129	0.8086	0.1499	0.8610	0.1021	0.9030	0.3622	0.6969	0.4358	0.6478
BackLeft-LeftShoulderBack-LeftUpperArmHigh	Mean	2	0.1312	0.8773	0.0324	0.9682	0.2414	0.7860	0.2599	0.7716	0.0830	0.9204	0.0986	0.9061	0.1756	0.8391
	SD	2	4.0633	**0.0229**	6.5990	**0.0027**	3.1264	**0.0481**	3.6658	**0.0282**	3.6448	**0.0288**	5.1320	**0.0073**	6.9080	**0.0014**
BackRight-RightShoulderBack-RightUpperArmHigh	Mean	2	1.0434	0.3595	1.3588	0.2653	0.0156	0.9845	0.3870	0.6799	0.3829	0.6826	0.3804	0.6844	0.4216	0.6569
	SD	2	0.5392	0.5864	3.1303	0.0514	0.3775	0.6866	1.9646	0.1442	1.7410	0.1794	2.4455	0.0910	2.0120	0.1382
BackTop-LeftShoulderBack-LeftUpperArmHigh	**Mean**	2	0.5789	0.5641	0.5947	0.5552	1.8350	0.1649	2.2422	0.1102	2.2731	0.1071	3.1222	**0.0476**	3.2399	**0.0426**
	SD	2	2.3301	0.1074	4.5964	**0.0142**	3.9456	**0.0224**	0.4238	0.6554	0.2227	0.8007	0.1632	0.8496	0.3666	0.6939
BackTop-RightShoulderBack-RightUpperArmHigh	Mean	2	0.3575	0.7012	0.2573	0.7740	0.6156	0.5424	2.8092	0.0638	2.6764	0.0726	2.9230	0.0576	2.6311	0.0761
	SD	2	3.1340	0.0519	6.6653	**0.0025**	0.9057	0.4076	0.2664	0.7666	0.7699	0.4652	2.2086	0.1143	3.1152	0.0479
LeftUpperArmHigh-LeftElbowOut-LeftWristOut	Mean	2	0.6176	0.5432	0.8131	0.4486	0.0917	0.9124	0.2894	0.7492	0.2457	0.7825	0.0682	0.9341	0.0836	0.9199
	SD	2	1.1964	0.3105	1.0386	0.3607	0.6048	0.5481	0.5018	0.6066	0.4446	0.6421	0.6856	0.5057	0.4640	0.6299
RightUpperArmHigh-RightElbowOut-RightWristOut	Mean	2	0.4218	0.6581	0.3834	0.6833	0.1244	0.8831	0.6790	0.5089	0.3996	0.6714	0.0878	0.9160	0.0227	0.9776
	SD	2	0.6450	0.5288	1.2455	0.2956	0.7447	0.4775	0.4103	0.6643	0.0592	0.9425	1.4991	0.2274	1.6201	0.2022

Table 3: Results of One-Way ANOVA for Mean and SD of Each Angle in Each Straightness Group for the Combination of Both Datasets (Factor: Expected Emotion)

Angle Name	**Type**	**Degree of Freedom**	**-35 to -25**		**-25 to -15**		**-15 to -5**		**-5 to 5**		**5 to 15**		**15 to 25**		**25 to 35**	
			F-Value	**P-Value**	**F-Value**	**P-Value**	**F-Value**	**P-Value**	**F-Value**	**P-Value**	**F-Value**	**P-Value**	**F-Value**	**P-Value**	**F-Value**	**P-Value**
LeftAnkleOut-LeftKneeOut-WaistLeftFront	Mean	2	0.8889	0.4142	0.5138	0.5996	0.4849	0.6166	0.5459	0.5802	0.3353	0.7156	1.1607	0.3159	0.3582	0.6995
	SD	2	0.1121	0.8940	0.2915	0.7477	1.1126	0.3311	0.7688	0.4650	0.4583	0.6331	0.4340	0.6486	0.3631	0.6961
RightAnkleOut-RightKneeOut-WaistRightFront	Mean	2	0.0329	0.9676	0.0472	0.9540	0.3526	0.7034	0.0121	0.9880	0.1759	0.8388	0.1320	0.8764	0.1424	0.8674
	SD	2	0.1325	0.8760	0.1906	0.8268	0.4201	0.6577	0.8706	0.4203	0.6268	0.5355	0.1002	0.9047	0.1900	0.8272
LeftShin-LeftKneeOut-LeftThigh	Mean	2	0.1249	0.8827	0.5342	0.5876	0.0607	0.9411	0.5588	0.5728	0.0567	0.9449	0.0076	0.9924	0.1155	0.8910
	SD	2	0.6168	0.5416	0.1971	0.8214	0.6260	0.5360	0.7648	0.4668	0.3290	0.7201	0.5040	0.6051	0.4124	0.6628
RightShin-RightKneeOut-RightThigh	Mean	2	0.0672	0.9351	0.0069	0.9932	0.2066	0.8135	0.3277	0.7210	0.2070	0.8132	0.0377	0.9630	0.1093	0.8965
	SD	2	0.0436	0.9573	0.7395	0.4796	0.2597	0.7716	0.9594	0.3849	0.9854	0.3753	0.0258	0.9745	0.4008	0.6705
LeftKneeOut-LeftThigh-WaistLeftFront	Mean	2	0.1201	0.8870	0.1752	0.8395	0.0038	0.9963	0.1161	0.8904	0.1711	0.8428	0.0372	0.9635	0.0106	0.9894
	SD	2	0.0760	0.9268	0.3010	0.7407	0.3138	0.7311	0.3577	0.6997	0.2497	0.7793	0.1087	0.8971	0.3529	0.7032
RightKneeOut-RightThigh-WaistRightFront	Mean	2	0.2374	0.7891	0.0815	0.9218	0.6413	0.5279	0.0821	0.9212	0.0503	0.9509	0.0196	0.9806	0.0110	0.9891
	SD	2	0.1190	0.8879	0.2379	0.7887	0.1215	0.8856	1.4663	0.2333	0.1899	0.8272	0.1518	0.8592	0.3705	0.6910
LeftThigh-WaistLeftFront-Chest	Mean	2	1.1409	0.3235	0.2564	0.7743	0.3969	0.6730	0.5684	0.5674	0.0562	0.9453	0.1529	0.8584	0.0840	0.9195
	SD	2	1.1551	0.3191	0.3157	0.7299	0.6249	0.5366	0.9654	0.3827	0.4013	0.6701	0.5218	0.5945	0.9062	0.4062
RightThigh-WaistRightFront-Chest	Mean	2	0.1304	0.8779	0.0182	0.9820	0.3002	0.7411	0.1972	0.8212	0.0171	0.9831	0.0076	0.9925	0.0408	0.9600
	SD	2	0.3824	0.6832	0.5041	0.6054	0.0192	0.9810	1.0753	0.3432	0.2323	0.7930	0.6501	0.5233	1.3587	0.2600
WaistLeftFront-Chest-LeftShoulderTop	Mean	2	0.1543	0.8572	0.2721	0.7623	0.4767	0.6217	0.1088	0.8970	0.1688	0.8448	0.3608	0.6977	0.1463	0.8640
	SD	2	1.2326	0.2958	0.8355	0.4363	0.0578	0.9439	0.1280	0.8799	0.4215	0.6567	1.1027	0.3345	1.4712	0.2328
WaistRightFront-Chest-RightShoulderTop	Mean	2	0.4412	0.6445	0.8631	0.4246	0.6562	0.5202	0.6426	0.5271	0.7795	0.4602	0.2226	0.8007	0.0892	0.9147
	SD	2	0.9805	0.3786	1.2926	0.2786	0.6135	0.5427	0.5156	0.5979	0.2326	0.7927	0.7737	0.4630	0.8033	0.4497
LeftKneeOut-WaistLeftBack-BackLeft	Mean	2	1.1029	0.3358	0.1450	0.8652	0.7232	0.4868	0.1525	0.8586	0.1163	0.8903	0.0637	0.9383	0.1709	0.8430
	SD	2	0.3811	0.6840	0.7816	0.4601	0.4158	0.6605	1.4025	0.2485	0.5700	0.5666	0.6148	0.5421	0.0348	0.9658
RightKneeOut-WaistRightBack-BackRight	Mean	2	0.4437	0.6429	1.0741	0.3450	0.4788	0.6204	0.6576	0.5193	1.4394	0.2399	1.1272	0.3265	0.7706	0.4645
	SD	2	0.0580	0.9437	0.2247	0.7991	0.6508	0.5230	0.6633	0.5163	0.5166	0.5974	0.1215	0.8857	0.3787	0.6854
WaistLeftBack-BackLeft-LeftShoulderBack	Mean	2	0.7470	0.4763	0.4246	0.6551	0.4929	0.6117	0.1985	0.8201	0.1539	0.8575	0.1087	0.8970	0.1956	0.8225
	SD	2	0.9215	0.4012	1.0748	0.3448	0.9873	0.3748	0.4754	0.6224	0.3996	0.6712	0.3071	0.7360	0.1608	0.8516
WaistRightBack-BackRight-RightShoulderBack	Mean	2	1.2878	0.2803	1.6770	0.1915	0.5412	0.5831	0.9541	0.3870	0.7541	0.4720	0.5657	0.5691	0.6158	0.5415
	SD	2	0.2144	0.8073	0.4039	0.6687	0.1699	0.8439	1.4352	0.2406	1.2506	0.2889	0.8578	0.4260	0.6100	0.5446
LeftShoulderBack-BackTop-HeadTop	Mean	2	0.0986	0.9062	0.1430	0.8669	0.1752	0.8394	0.4419	0.6435	0.1602	0.8521	0.2442	0.7836	0.0969	0.9077
	SD	2	0.4353	0.6482	0.2140	0.8077	0.5692	0.5671	0.7252	0.4855	2.0657	0.1298	0.2871	0.7509	0.2208	0.8022
RightShoulderBack-BackTop-HeadTop	Mean	2	0.0280	0.9724	0.1260	0.8817	0.0879	0.9159	0.1108	0.8951	0.0867	0.9170	0.0039	0.9961	0.1376	0.8715
	SD	2	0.1433	0.8667	0.1829	0.8331	0.3781	0.6858	1.4677	0.2330	0.5020	0.6062	0.9158	0.4023	1.1076	0.3329
BackLeft-BackTop-HeadTop	Mean	2	0.1497	0.8612	0.0112	0.9888	0.3020	0.7397	0.5168	0.5973	0.5610	0.5717	0.6829	0.5066	0.7499	0.4741
	SD	2	0.5434	0.5824	0.2992	0.7420	0.5753	0.5637	2.0102	0.1367	1.0879	0.3392	0.4158	0.6605	0.2432	0.7844
BackRight-BackTop-HeadTop	Mean	2	0.5334	0.5882	0.4548	0.6357	0.6570	0.5198	0.5928	0.5538	0.4129	0.6624	0.0418	0.9591	0.0796	0.9235
	SD	2	1.1313	0.3266	0.7431	0.4779	0.5569	0.5741	0.4382	0.6458	0.3703	0.6911	0.4673	0.6275	0.4228	0.6560
BackLeft-LeftShoulderBack-LeftUpperArmHigh	Mean	2	0.6108	0.5448	1.6616	0.1944	0.4692	0.6263	0.1835	0.8325	0.3782	0.6857	0.7477	0.4751	0.0784	0.9247
	SD	2	1.3979	0.2517	0.4699	0.6263	1.4076	0.2476	0.1857	0.8307	1.9177	0.1501	1.7194	0.1825	3.0666	**0.0494**
BackRight-RightShoulderBack-RightUpperArmHigh	Mean	2	0.5394	0.5848	0.6176	0.5410	0.3516	0.7041	0.6510	0.5227	0.9344	0.3948	0.2527	0.7770	0.8917	0.4121
	SD	2	1.0601	0.3502	1.4904	0.2296	0.2017	0.8175	0.7883	0.4561	0.3443	0.7092	0.3478	0.7068	0.8807	0.4166
BackTop-LeftShoulderBack-LeftUpperArmHigh	Mean	2	0.2856	0.7521	0.2597	0.7718	0.1562	0.8555	0.0687	0.9336	0.1016	0.9035	0.3361	0.7151	0.2912	0.7478
	SD	2	0.5851	0.5588	0.1735	0.8410	0.4041	0.6683	0.1264	0.8813	0.4219	0.6565	1.1095	0.3323	0.6199	0.5393
BackTop-RightShoulderBack-RightUpperArmHigh	Mean	2	1.3145	0.2731	1.2619	0.2870	0.5436	0.5817	1.1560	0.3169	0.3471	0.7072	0.5254	0.5923	0.5564	0.5744
	SD	2	1.2119	0.3018	1.0990	0.3367	0.5272	0.5913	0.9254	0.3981	0.2154	0.8065	0.8897	0.4128	1.0871	0.3398
LeftUpperArmHigh-LeftElbowOut-LeftWristOut	Mean	2	0.1971	0.8214	0.0242	0.9761	0.1819	0.8338	0.0665	0.9357	0.2760	0.7591	0.2202	0.8026	0.0319	0.9686
	SD	2	0.4282	0.6528	0.3600	0.6985	0.1747	0.8399	0.3958	0.6737	0.9238	0.3990	0.8483	0.4301	0.9324	0.3958
RightUpperArmHigh-RightElbowOut-RightWristOut	Mean	2	0.5244	0.5935	0.4448	0.6421	0.3241	0.7237	0.3516	0.7040	0.4508	0.6379	0.1334	0.8752	0.0425	0.9584
	SD	2	0.1984	0.8204	0.6765	0.5104	0.0870	0.9167	0.1531	0.8582	0.4728	0.6241	0.0255	0.9748	0.2700	0.7638

Table 4: Results of One-Way ANOVA for Mean and SD of Each Angle in Each Straightness Group for the Combination of Both Datasets (Factor: Reported Emotion)

Angle Name	Type	Degree of Freedom	-35 to -25		-25 to -15		-15 to -5		-5 to 5		5 to 15		15 to 25		25 to 35	
			F-Value	P-Value	F-Value	P-Value	F-Value	P-Value	F-Value	P-Value	F-Value	P-Value	F-Value	P-Value	F-Value	P-Value
LeftAnkleOut-LeftKneeOut-WaistLeftFront	Mean	2	2.1083	0.1266	0.4769	0.6220	1.0672	0.3463	0.3923	0.6760	0.3252	0.7228	1.5376	0.2181	0.2862	0.7515
	SD	2	0.0872	0.9166	0.5682	0.5682	0.1685	0.8450	1.1179	0.3291	0.9840	0.3759	3.7187	**0.0264**	2.1478	0.1202
RightAnkleOut-RightKneeOut-WaistRightFront	Mean	2	0.6807	0.5085	1.1767	0.3120	0.8529	0.4280	0.0673	0.9349	0.7639	0.4674	0.0687	0.9336	0.0862	0.9175
	SD	2	0.1069	0.8987	1.2682	0.2853	1.4688	0.2332	2.6926	0.0702	1.4119	0.2465	2.2237	0.1115	3.0605	**0.0497**
LeftShin-LeftKneeOut-LeftThigh	Mean	2	0.2280	0.7965	1.7758	0.1741	0.1895	0.8275	1.3973	0.2497	0.3855	0.6807	0.4432	0.6428	0.7890	0.4561
	SD	2	1.4920	0.2297	1.7480	0.1788	1.4156	0.2457	0.8242	0.4401	0.4422	0.6434	0.9726	0.3803	1.0468	0.3535
RightShin-RightKneeOut-RightThigh	**Mean**	2	1.6507	0.1969	2.5729	0.0807	2.1315	0.1219	2.1268	0.1220	2.7356	0.0676	3.2877	**0.0399**	2.3955	0.0945
	SD	2	1.7456	0.1796	0.9101	0.4054	1.7572	0.1757	1.0265	0.3602	0.2984	0.7424	0.1865	0.8301	1.3122	0.2722
LeftKneeOut-LeftThigh-WaistLeftFront	Mean	2	1.1154	0.3317	0.6901	0.5036	0.6272	0.5354	1.6249	0.1996	0.5365	0.5858	0.7797	0.4603	1.4582	0.2358
	SD	2	0.2681	0.7653	0.5342	0.5876	2.0076	0.1376	0.2554	0.7748	0.2342	0.7915	0.2013	0.8179	0.0268	0.9736
RightKneeOut-RightThigh-WaistRightFront	Mean	2	1.7377	0.1810	1.4680	0.2347	1.5358	0.2183	1.5908	0.2064	0.9111	0.4040	2.3829	0.0955	1.7646	0.1747
	SD	2	0.9003	0.4096	0.5928	0.5544	0.6850	0.5055	2.3039	0.1026	0.1579	0.8541	0.3096	0.7342	0.4957	0.6101
LeftThigh-WaistLeftFront-Chest	Mean	2	2.0755	0.1307	0.5832	0.5598	0.4939	0.6111	2.8797	0.0586	1.1636	0.3148	1.7307	0.1805	1.4207	0.2447
	SD	2	0.1939	0.8240	0.2681	0.7653	1.6894	0.1878	0.6471	0.5247	1.3707	0.2567	0.7880	0.4565	0.1560	0.8557
RightThigh-WaistRightFront-Chest	Mean	2	0.0896	0.9144	0.0812	0.9221	0.6346	0.5314	0.0947	0.9097	0.0616	0.9403	0.4532	0.6364	0.4177	0.6593
	SD	2	0.0931	0.9112	0.5411	0.5836	0.7828	0.4588	3.4262	**0.0345**	1.0254	0.3608	0.5228	0.5938	0.1496	0.8612
WaistLeftFront-Chest-LeftShoulderTop	Mean	2	0.6266	0.5364	0.4000	0.6713	0.7515	0.4732	1.5884	0.2069	0.8913	0.4120	1.2366	0.2931	0.6715	0.5124
	SD	2	1.9948	0.1413	1.6130	0.2038	0.9626	0.3840	0.6480	0.5242	0.4517	0.6373	0.4168	0.6599	0.7392	0.4791
WaistRightFront-Chest-RightShoulderTop	Mean	2	0.3789	0.6856	0.4800	0.6200	0.2180	0.8044	0.3510	0.7044	0.3130	0.7316	0.1059	0.8996	1.1743	0.3118
	SD	2	1.1997	0.3055	1.8652	0.1596	0.3560	0.7010	0.4153	0.6607	0.0298	0.9706	1.1848	0.3085	1.1203	0.3288
LeftKneeOut-WaistLeftBack-BackLeft	**Mean**	2	0.8965	0.4112	0.4035	0.6689	0.7141	0.4912	4.4613	**0.0128**	3.3535	**0.0372**	4.2417	**0.0160**	3.0949	**0.0481**
	SD	2	2.4200	0.0940	2.2950	0.1054	2.5008	0.0851	0.5398	0.5838	0.7113	0.4924	1.3826	0.2539	0.8733	0.4196
RightKneeOut-WaistRightBack-BackRight	**Mean**	2	2.0322	0.1363	3.6744	**0.0284**	2.2884	0.1047	4.0624	**0.0187**	3.8022	**0.0242**	2.0422	0.1331	2.0828	0.1280
	SD	2	0.1611	0.8514	0.6278	0.5356	0.3495	0.7056	0.2771	0.7583	0.3963	0.6734	0.0710	0.9315	0.2152	0.8067
WaistLeftBack-BackLeft-LeftShoulderBack	Mean	2	1.2163	0.3005	1.1312	0.3262	1.6084	0.2033	1.7501	0.1765	1.5008	0.2258	2.1981	0.1144	1.6682	0.1919
	SD	2	0.3966	0.6736	0.6943	0.5015	0.6353	0.5311	0.4166	0.6599	0.8811	0.4162	0.5300	0.5897	0.4119	0.6631
WaistRightBack-BackRight-RightShoulderBack	**Mean**	2	2.1893	0.1172	3.4134	**0.0363**	2.6253	0.0755	3.1112	**0.0468**	3.9673	**0.0207**	2.0531	0.1317	2.3080	0.1028
	SD	2	0.2469	0.7816	0.5137	0.5996	0.0777	0.9252	0.1602	0.8521	0.0131	0.9870	0.2289	0.7957	0.2877	0.7504
LeftShoulderBack-BackTop-HeadTop	Mean	2	0.7262	0.4862	0.8549	0.4280	1.3984	0.2499	1.5517	0.2145	1.3629	0.2586	1.4459	0.2386	2.1129	0.1243
	SD	2	0.0713	0.9312	0.7052	0.4961	0.5870	0.5572	0.1153	0.8911	0.9725	0.3802	0.2636	0.7686	0.3335	0.7169
RightShoulderBack-BackTop-HeadTop	Mean	2	1.5606	0.2149	2.2129	0.1141	2.1251	0.1227	2.4146	0.0921	1.8733	0.1567	1.9091	0.1516	2.2146	0.1126
	SD	2	0.5512	0.5779	0.6911	0.5031	1.6956	0.1867	1.4619	0.2343	0.6181	0.5401	0.7987	0.4517	1.5899	0.2072
BackLeft-BackTop-HeadTop	Mean	2	1.1731	0.3135	1.7824	0.1729	1.1750	0.3114	0.7639	0.4672	1.5038	0.2252	1.2742	0.2825	2.0429	0.1331
	SD	2	0.3430	0.7105	0.6242	0.5375	3.7010	**0.0268**	0.4342	0.6484	0.6477	0.5245	0.4798	0.6198	0.2636	0.7686
BackRight-BackTop-HeadTop	Mean	2	1.3631	0.2604	1.7396	0.1802	0.9995	0.3703	0.3298	0.7194	0.9706	0.3809	0.3500	0.7052	0.3559	0.7011
	SD	2	0.4215	0.6572	0.1280	0.8800	1.2939	0.2770	0.7979	0.4517	0.3034	0.7387	0.6735	0.5113	0.6832	0.5065
BackLeft-LeftShoulderBack-LeftUpperArmHigh	Mean	2	0.6035	0.5488	0.0022	0.9978	0.0231	0.9772	0.2776	0.7579	0.0147	0.9854	0.0920	0.9121	0.0257	0.9747
	SD	2	2.4124	0.0946	0.4531	0.6368	0.1236	0.8838	0.8461	0.4307	2.3878	0.0949	2.1825	0.1161	6.3311	**0.0023**
BackRight-RightShoulderBack-RightUpperArmHigh	Mean	2	1.5640	0.2142	1.4495	0.2390	0.8507	0.4290	0.8189	0.4425	0.9847	0.3756	0.6724	0.5119	0.3588	0.6991
	SD	2	2.0030	0.1401	4.7092	**0.0108**	1.9967	0.1391	0.0494	0.9518	1.8799	0.1557	0.7719	0.4638	1.8260	0.1645
BackTop-LeftShoulderBack-LeftUpperArmHigh	Mean	2	0.5664	0.5693	1.8377	0.1639	2.8643	0.0598	1.4528	0.2364	2.5652	0.0798	2.9395	0.0558	2.4916	0.0861
	SD	2	0.0219	0.9784	0.4384	0.6461	0.2614	0.7703	0.4894	0.6137	0.2062	0.8139	0.1850	0.8313	0.2889	0.7495
BackTop-RightShoulderBack-RightUpperArmHigh	**Mean**	2	2.3461	0.1008	2.5208	0.0849	3.2519	**0.0412**	2.7417	0.0670	2.2603	0.1074	3.1329	**0.0463**	2.6921	0.0709
	SD	2	6.6444	**0.0019**	4.4735	**0.0135**	1.1185	0.3293	0.1016	0.9035	0.3731	0.6892	0.0469	0.9542	2.4614	0.0886
LeftUpperArmHigh-LeftElbowOut-LeftWristOut	Mean	2	0.2683	0.7652	0.1242	0.8833	0.7070	0.4947	0.3079	0.7353	0.1052	0.9002	0.5953	0.5527	0.1942	0.8237
	SD	2	2.4322	0.0929	1.3767	0.2567	0.2055	0.8145	0.7617	0.4683	0.1849	0.8314	0.3769	0.6866	0.2322	0.7931
RightUpperArmHigh-RightElbowOut-RightWristOut	Mean	2	0.4759	0.6227	0.4203	0.6578	0.1168	0.8898	0.0719	0.9306	0.2151	0.8067	0.1754	0.8393	0.0700	0.9324
	SD	2	1.0803	0.3433	1.6013	0.2062	0.5197	0.5956	1.2047	0.3020	0.5978	0.5511	2.5795	0.0790	2.8126	0.0631