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Biomechanical Analysis of Manual Operations for Touchscreen Interface

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Abstract

Biomechanical Analysis of Manual Operations for Touchscreen Interface

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Human hands are the most sophisticated and functional organ. The human hands are, therefore, the most effective and powerful tool to do operations with various hand devices. One of the most common hand devices in the present day would be a smartphone, which is a handheld-sized touchscreen device. The previous studies on the handheld touchscreen devices focused on the thumb operations or reach zones by measuring individual muscle or joint angle. However, they were limited to thumb operations and did not consider grasping. They also did not explain hand motion in the aspect of motor control, which coordinates muscles and joint angles simultaneously.

As one of the predominant theoretical frameworks for motor control, dynamic systems theory suggests human motion in the following perspective; a motion is produced from the interaction of subsystems within individuals, tasks, and the

environment. According to the theory, physical/anthropometrical properties of the human can be one of constraints that limit the movements and the human motion is explained by a concept called "synergy" which is a coordination of muscle activities or joint angles.

The purpose of this dissertation was to analyze the hand motions including grasping the handheld touchscreen devices and the thumb operations during performing the representative interactions. Anthropometrical characteristics of hands, as one of the constraints of the hand motion, were considered in the motion analysis.

In order to achieve the goal of this dissertation, firstly, the hand was classified after selecting hand dimensions which were related to the use of the devices. After dimension reduction, three common clustering methods, k-means, fuzzy c-means and latent profile analysis were applied and the results were compared to each other. The hand types were defined based on the result of cluster analysis.

Secondly, to analyze grasping the handheld touchscreen device, it was required to compare the grasp of the device to other grasps in the existing grasp taxonomy. In order to achieve this goal, the followings were accomplished: 1) defining muscular and postural synergies through dimension reduction technique, 2) identifying the grasp in the existing taxonomy in terms of the synergies, 3) attempting to allocate the grasp of the handheld touchscreen device to the taxonomy and 4) figuring out the difference between the hand types defined from the previous part.

Thirdly, the thumb operations and the grasp were investigated in terms of the muscular and postural synergies. Two tasks, dragging and tapping tasks which were

the most frequently used interactions for the touchscreen devices, were involved in the experiment.

Analyzing human motion is helpful to understand motor control strategies. The expected contributions of the research are: better understanding of hand motions for using handheld touchscreen devices, designing better interactions for a smartphone or other small touchscreen devices and applying the synergies defined in this dissertation to design robot hands or prosthetic hands dealing with a problem of degree of freedom redundancy.

Keywords: human hand, handheld touchscreen devices, grasp taxonomy, hand classification, muscular synergy, postural synergy

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Chapter 1. Introduction

1.1 Research Background

Human hands are the most sophisticated organ in the aspect of function and dexterity. With 27 bones and 14 phalanges of the fingers and thumb, a hand has an almost infinite number of degrees of freedom. The human hand is, therefore, the most effective and powerful appendage which can operate various kinds of hand tools.

Many studies were conducted on structure, function and motion of hands; they inquired an anatomical or musculoskeletal aspect [1, 2], an anthropometrical aspect [3-5], and a functional aspect for use of tools or instruments of hands [6-8]. There were also some studies which analyzed hand motion for clinical rehabilitation [9, 10], sports performance [11, 12], manual works [13, 14] or movement strategy [15]. They explored, predicted and simulated the motions through employing various techniques.

Researches about human hands have been targeted specific hand tools from traditional farming tools [16] to recently, touchscreen devices [17-19]. The purposes of these studies were from improving hand tools to reduce fatigue in hands to understanding hand motion patterns. Developing new hand tools or devices can also be the research topic.

One of the most common hand devices people use in the present day would be a smartphone, which is a handheld-sized touchscreen device. Smartphone usage is penetrated in contemporary times. Recent data showed that the average worldwide

ownership rate of a smartphone is 43% [20], with 82.2%, 72.9% and 71.5% ownership in United Arab Emirates, South Korea and the United States [21]. A well-designed device can promote performance and user experience, and reduce strain on the musculoskeletal system [22]. For this reason, considering the smartphone usage growth, it is necessary to understand human hand motion when using the devices for designing the form factors, user interface, or a keypad.

Smartphones may induce usability issues because of its physical properties. In practice, the handheld-sized touchscreen devices are one-size products; no adjustability is allowed. Also, all devices have been shaped as a thin and rectangular parallelepiped with little variations. These uniformities are less likely to accommodate all user populations considering huge diversity of human hands.

Previous studies on the handheld touchscreen devices or the old cell phones focused on the form factors: the size of the device, location of physical buttons, thumb operations, a thumb envelope, screen layouts including size and location of soft keys or icons. However, there are several limitations that previous researches had in common.

Firstly, only a few of them considered the effect of hand shape. According to the previous studies, hand length differed users' satisfaction or hand muscle activities [23], but even those studies rarely considered the shape of hands as an influential variable. It seems natural that hand length may not be the only hand dimensions which can affect handheld device usage in terms of satisfaction or hand muscle activities.

Secondly, most previous studies focused on only thumb operations when using

smartphones [24–32]. It is because the thumb is the most important digit when operating touchscreen devices, especially, with a single hand. Some had considered indicating finger together with a thumb, but not whole fingers [33]. In fact, together with the thumb, other fingers work as well to stably grasp the device during operating the device.

Thirdly, useful methodologies or analysis techniques were not applied to hand motion analysis in together. Even though the dynamic pattern or muscular/postural synergy are very important in understanding human hand behaviors, most previous researches did not apply the concept to conduct researches on the hand–held device. The results just have focused on analyzing each muscle or joint angle separately.

In this research, hand motions including grasp during handheld device operations will be analyzed. Anthropometrical characteristics of hands were also considered in terms of muscular/postural synergies. In the following sections, the research questions to be addressed in this dissertation will be stated.

1.2 Research Questions

In this section, four fundamental research questions representing the research objective are listed. In the last chapter, these research questions will be revisited to explain how they are handled through this research. The followings are the four main research questions examined in this dissertation:

Research Question 1: What is the most appropriate method to classify human hand types?

Research Question 2: Can the touchscreen device grasp posture be explained by hand grasp class of the existing taxonomy? Does a data-driven classification differ from existing grasp classification with top-down approaches?

Research Question 3: How the hand type affect hand operations when using the touchscreen devices considering with the physical properties of the device and tasks?

Research Question 4: How the result can be interpreted and applied in a practical way?

1.3 Document Outline

This dissertation is organized from answering the research questions mentioned above. The dissertation consists of six chapters including this introductory chapter. Each chapter is composed of its own introduction, method, results, conclusions and discussion. Brief descriptions of the subsequent parts are presented below.

Chapter 2 provides literature reviews for this dissertation. It begins by laying out the structure and function of human hands to explore muscles and joints related to touchscreen devices use. The selected muscles and joints will be measured in experiments. Also, the theoretical bases of motor theory will be introduced by explaining a concept which is called "synergy" with its usefulness. Additionally, main constraints in a motor theory, which is a dynamic systems theory, will be described. Then, researches which are relevant to hand anthropometry will be introduced. In the last two subsections, existing studies on hand grasp taxonomies and touchscreen devices interaction will be reviewed to refer to research methodologies as well as to investigate their limitations. Based on the results of the literature review, experiments will be designed and the results will be analyzed.

In Chapter 3, hand type will be classified with selected hand dimensions which are related to using of the devices. To select the most appropriate method for the hand classification, analysis techniques will be explored. Several clustering algorithms will be compared through cluster validation index.

Chapter 4 explains experimental designs including designing customized

measuring system to define muscular and postural synergies. Two tasks, grasp and manual operation for a touchscreen device, will be performed to define the synergies. A relationship between two synergies will be analyzed as well. In later chapters, results of hand motions will be analyzed in terms of these synergies defined in Chapter 4.

In Chapter 5, existing grasp taxonomy will be re-classified according to hand grasp data. The existing grasp classification results were established by top-down method considering grasping hand posture, the direction and its origin of pressure, task types or the types of object to be grasped. Both joint angle and muscle activity data will be considered as a form of synergy to classify grasp types. An effect of hand type will be considered as well. In addition to re-classification, it will be attempted to allocate a grasp specified to the touchscreen devices into the existing taxonomy.

Chapter 6 aims to determine operational motions of a hand during hand-held touchscreen device use. The effect of hand types, task types and levels of the tasks will be considered. The synergies which compose this operational motion will be compared according to the task types and hand types, too.

Finally, the dissertation will be concluded with a brief summary and critique of the findings in Chapter 7. Also, discussions on the implication of the findings and limitations will be addressed indicating future research directions.

Chapter 2. Literature Review

2.1 Structure and Function of Human Hand

The human can do a number of sophisticated manual tasks in their lives. A human hand has a highly complex structure which is made up of five digits. Each consists of a collection of bones, muscles, ligaments, tendons, and vascular structures enclosed by skin. Due to the complexity, a human can operate hands in a diverse way. In Section 2.1, the structure and function of hand will be described.

2.1.1 Hand joints

A human hand consists of three types of bones, carpal bones, metacarpal bones and phalanges. The total number of hand bones is 27 including 14 phalanges of the fingers and thumb. Phalanges are the bones that make fingers and toes and have three types: proximal, intermediate and distal. In this order, the phalanges are in close proximity to the hand. The metacarpal bones connect the fingers and the carpal bones of the wrist. The hand has five metacarpals and eight carpal bones as shown in Figure 1. The eight short carpal bones of the wrist are organized into a proximal row (scaphoid, lunate, triquetral and pisiform) which articulates with the bones of the forearm, and a distal row (trapezium, trapezoid, capitate and hamate), which articulates with the bases of the five metacarpal bones of the hand. The heads of the metacarpals will each in turn articulate with the bases of the proximal phalanges of the fingers and thumb. These articulations with the fingers are the metacarpophalangeal joints known as the knuckles. The types of articulations are: 1)

interphalangeal articulations of hand which are the hinge joints between the bones of the digits which are proximal interphalangeal joints (PIP) and distal interphalangeal joints (DIP), 2) metacarpophalangeal joints (MP or MCP) where the digits meet the palm and 3) intercarpal articulations where the palm meets the wrist. Having only two phalanges, proximal and distal, a thumb has one interphalangeal (IP) joint.

The joints are in charge of rotation and movement of the thumb and fingers. For instance, MCP and IP joints of the thumb mainly assist extension and flexion. In the case of fingers, flexion, extension, hyperextension, abduction and adduction occur at MCPs. PIPs and DIPs of fingers are uniaxial hinge joints so that they flex and extend fingers. According to the previous researches, it was found that DIP angels can be predicted through PIP angles by establishing a mathematical model. In many studies, angles of MCPs and PIPs including IP were dealt to analyze hand motions. Data glove is one of the systems that measures joint angle or flection-extension of fingers. However, this device may hinder natural movement due to elasticity of textile structure or sensors.

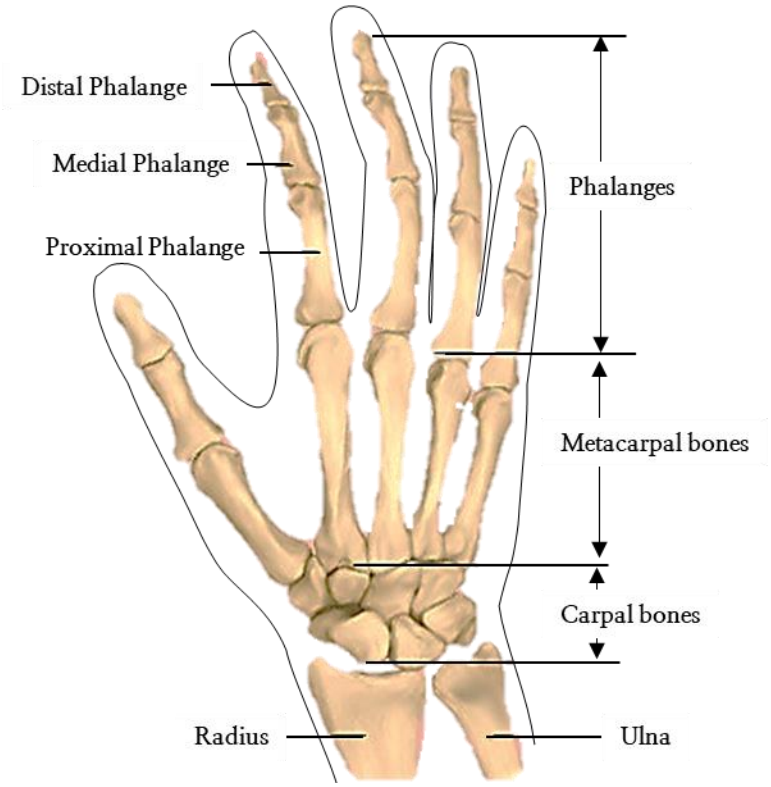


Figure 1. Illustration of bones and joints of a hand

2.1.2 Hand muscles

The muscles of the hand are responsible for the movement of the hand and fingers as skeletal muscles attached to bones. There are 35 muscles operating human hands [34]. The muscles of the hand can be divided into two groups: extrinsic and intrinsic muscle groups.

The extrinsic muscles of the hand have long tendons connecting the muscles to bones of the hand. The extrinsic muscle group includes the long flexors and extensors. "Extensor" denotes their action which is to extend joints of the hand and "flexor" refers to flexing them. They can be again divided into anterior and posterior muscles. Some examples of the anterior extrinsic muscles of the hand are flexor digitorum superficialis (FDS) and flexor digitorum profundus (FDP); FDP activates when DIPs flex. FDS is a muscle of the fingers acting on the PIP joints flexion. The examples of posterior extrinsic muscles are extensor digitorum (ED) and abductor pollicis longus (APL). ED moves the proximal phalanges to extend the MCP joints. Although it is extrinsic, APL abducts the thumb acting to the wrist. The extrinsic muscles are located on the back of the forearm and outside of the hand as the term suggests.

In contrast, the intrinsic muscles refer to smaller muscles located within the hand. The intrinsic muscles include thenar (thumb) and hypothenar (little finger) muscles; four dorsal and three palmer interosseous muscles originating between the metacarpal bones; and four lumbrical muscles arising from the deep flexor to flex MCP joints and extend IP joints of fingers [35]. The lumbrical muscles are distinguished due to the non-bony origin. Flexor pollicis brevis (FPB) and abductor pollicis brevis (APB)

belong to thenar muscles. First dorsal interosseous (FDI) which is located between the adjacent surfaces of the thumb and index metacarpals is an example of dorsal interosseous muscles. Figure 2 describes intrinsic muscles of a hand.

In experiments conducted in this dissertation, the activity of the muscles mentioned above will be measured except FDP; FDP will be excluded because surface electromyography (sEMG) of which signal indicates muscle activities does not accurately assess FDP activity [36]. Other muscles are available to measure using sEMG. However, operating device with attaching electrodes of sEMG can be a challenge to participants due to the location of the intrinsic thenar muscles.

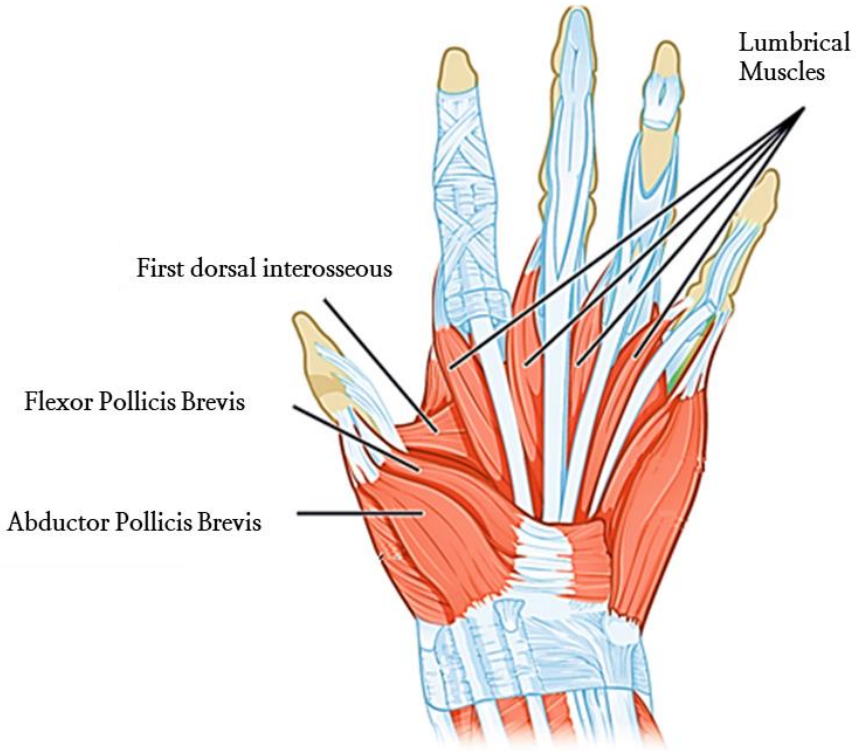


Figure 2. Palmer view of a left hand

2.1.3 Hand functions

Humans possess a special function with an opposable thumb to the other four fingers. Thumb which accounts for 40% and even more of overall hand use allows the unique motion, for example, opposition/reposition [37, 38]. The thumb opposition refers to one kind of motion that thumb reaches each fingertip of the same hand with some power by turning and rotating it. The thumb opposition results from flexion, abduction and axial rotation at the carpometacarpal (CMC), MCP, and IP joints. The axis of rotation of the thumb is founded in the trapezoidal metacarpal joint. This unique position allows for circulation operations of the thumb and consequently for the opposition of the thumb to other digits. Figure 3 illustrates the thumb and finger motions.

The primary function of the human hand is prehension meaning to grasp and operate/manipulate objects. It is the opposable thumb that allows us to grasp objects of various sizes, to operate tools and to exploit our dexterity to its fullest extent. This hand function separates man from primates, who possess five digits but without opposition, and makes humans have the advance functioning capability as toolmakers.

Grasping, one of the main functions of hand, is a result of co-activating muscles, tendons and joints of a hand. Four fingers move simultaneously. Chao [39] reported that extrinsic muscles work across two or more joints, usually causing the tendons to penetrate the joints or cross the joints without attaching to the bone elements. The tendons of the FDP penetrate the MP and PIP joints and are inserted into the base of the distal phalanges. This is involved in the movement of the PIP and DIP joints but

not in the MP movement.

Thumb is independently operated by muscles such as APB, APL or FPB. While grasping a device or tool, the thumb can be operated alone without dropping due to these muscles. Also, the fingers of the hand can move differently depending on the given posture of the hand.

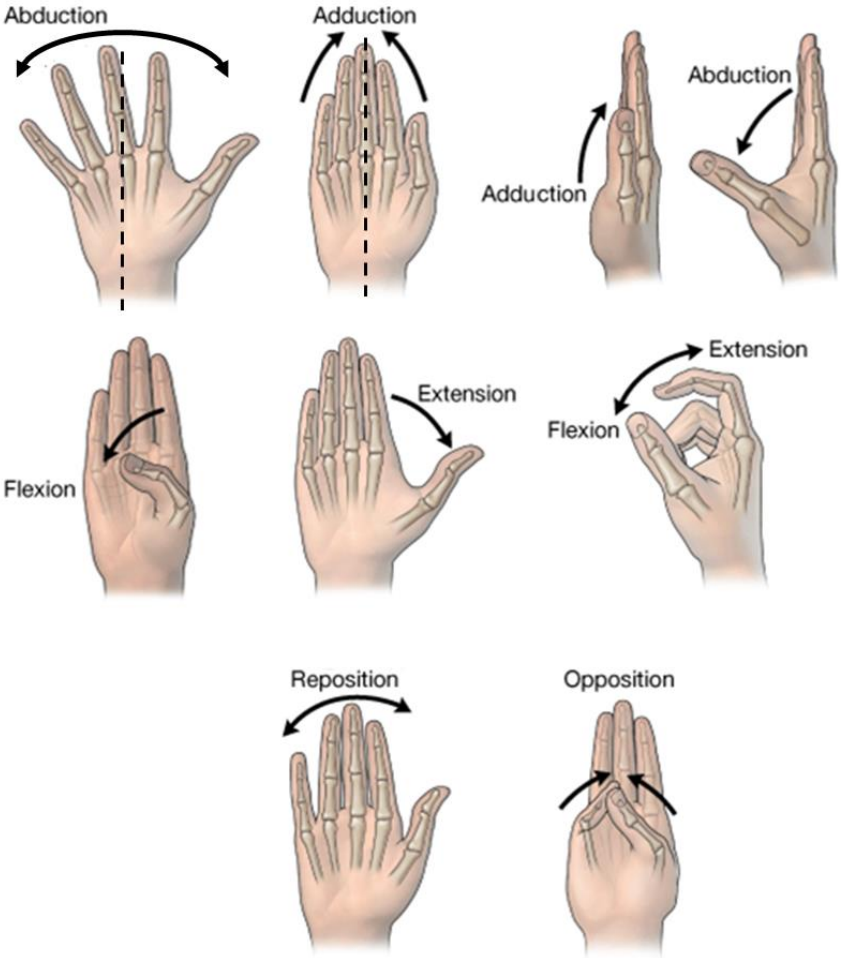


Figure 3. Thumb and finger motions: adduction – abduction (top), flexion – extension (middle) and reposition – opposition (bottom)

2.2 Motor Control Theory

In order to function hand precisely, like other body movements, the central nervous system (CNS) controls a motion of hands. Currently, there is no agreed model to explain how the hand is controlled by the brain, and the model referred to as "motor control". There are, however, some convincing theories of controlling motion, called motor control theories. Two key questions to be addressed by the motor control theory are: 1) how humans coordinate motion and 2) how they eliminate the redundancy of degrees of freedom. The details of the motor theory and relative materials used in the following chapters are explained in Section 2.2.

2.2.1 General motor theory

A motion is an outcome that motor control takes. Many researchers have studied the motion to understand how humans control them. Motor control is a relatively recent research topic to explore how CNS produces purposeful and coordinated movements in interaction with the rest of the body and with the environment. The researches have also focused on solving motor redundancy or degrees of freedom problem (DOF); how does the brain choose a solution among an infinite set of redundant designs of body coordination? Motor control theories account for this question to solve the DOF problem.

There are several theories of motor control. The theories of human motion control have been established in many different ways by suggesting different clinical implements since the 19th century. The examples of approaches that motor control

theories take are information processing approach (e.g. motor programs theory), dynamic systems approach (e.g. dynamic systems theory and ecological theory) and computational approach (e.g. adaptive model theory). The first two approaches are based on the behavioral level and the last one addresses the neural level. Two predominant theoretical frameworks for motor control are based on perspectives of the motor program and dynamical systems (or dynamic pattern) theories [40].

A motor program is a series of subroutines that are organized in a specific order, stored in long-term memory, and retrieved when performing an action. The motor program theory describes that humans control their motions based on this pre-structured motor program. Although this programming theory can explain some aspect of human motions, this theory does not deal with human variability well.

The dynamic systems theory analyzes human motion from a different perspective; a motion is produced through the interaction of subsystems of individuals, tasks and the environment. All subsystems voluntarily interact and self-organize in a particular way to perform the most efficient motion for a given task [41]. The dynamic systems theory can explain the non-linearity of movement without a memory limit problem, which the motor program theory has.

2.2.2 Dynamic systems theory

In the dynamic systems theory, constraints cause different coordination of movements. There are mainly three types of constraints in the dynamic systems theory: 1) environment, 2) tasks and 3) organism constraints [42]. The environmental constraints are physical and sociocultural constraints from outside of the body, for

example, gravity, temperature, gender roles and cultural norms. The task constraints are also from outside of the body and related to a specific task or skill such as the goal of a task and rules about performance or equipment. The constraints of organism refer to various properties that humans have. Examples of organism constraints, which consist of structural and functional constraints, are cognitive, emotional, and psychological properties as well as physical/anthropometric properties such as height and body shape of humans. Humans control their motions appropriately within the interactions among such constraints.

From the explanation of organism constraints, it can be inferred that the physical property of human limits their motions. However, the existing studies did not sufficiently analyze the effect of the organism constraints related to physical factors of the body on motion strategy or consequence of movement. An academic field which deals with such property of human through scientific methodology is called "Anthropometry". In this dissertation, anthropometry of hand will be taken into account to investigate hand motions.

DOF is another problem of controlling movement coordination. Bernstein, in dynamic systems theory, approached the question of controllability of all our motor units, muscles, and joints from an integrated perspective in which biomechanical, neural, and physiological constraints interact. The key research questions raised by Bernstein inspired new ways of research into how people learn complex patterns of coordination [43, 44]. The question how individuals learn to integrate and coordinate the multiple degrees of freedom is not only important for the analysis of elite performance such as that of athletes or skilled musicians but also relevant for a better

understanding of coordination problems in individuals with movement disabilities.

Infinite degrees of freedom are given to individuals in controlling motion. However, a limited number of combinations are actually selected for operation. An initial approach to finding the reason for this is to assume a coordinative structure or pattern reduces some portion of DOF. The concept of the coordinative structure or movement pattern is called "synergy".

2.2.3 Muscular and postural synergies

The large numbers of mechanical DOF of the hand are not fully applied during actual movements such as grasping. The concept of synergy was one of the most used to analyze muscular and postural coordinated activation during grasping. In general, angular movements of various joints tend to be combined, and muscle activity in various hand muscles tend to correlate. The occurrence of covariation in the joints was defined as kinematic or postural synergy and one in the muscles is called as muscular synergies [45]. Fingers move or exert force in a fewer number of postural and muscular coordination patterns (or synergies) than a number of possible degrees of freedom for mechanical and muscular control in grasping.

In previous studies, one of the main problems to analyze the hand in the biomechanical and behavioral aspects was the high redundancy of its structure. In other words, same as other body parts, the hand has much more degrees of freedom than actually required or used ones. In these cases, the concept of synergies could be used to cope with functional dependencies of degrees of freedom. According to Santello [46], the simultaneous motion of fingers was explained by the reduced number

of independent coordination and covariation patterns, which were synergies. Other evidence of synergy for hand motion was found in other researches [47–49].

As mentioned above, there are two types of synergies, muscular and postural synergies. Muscular activities which are the components of muscular synergy can be measured in the simplest way through sEMG [50]. Therefore, sEMG can be utilized to identify the muscular synergies during hand grasping by recording the electrical activity produced by skeletal muscles [51].

Postural synergy is defined as a pattern of simultaneous displacement of body parts. Postural synergy is sometimes mingled with kinematic synergy. In grasping tasks, the synergies can be defined based on joint angles of fingers and thumb [52, 53].

Both muscular and postural synergies can be achieved from dimension reduction techniques without losing information that the original data contains. One example of a data reduction method is principal component analysis (PCA) which linearly maps the data to a lower-dimensional space in a manner that maximized the variance of the data dimensional. Existing studies mainly applied PCA method to transform muscle activities or joint angles to the corresponding synergies [45, 51, 53, 54].

It is compelling that synergy control of the hand may not only represent an effective theoretical approach to explain how the CNS solves the redundancy problem, but may also characterize the way in which motions and movements are represented at the neural level. Therefore, it will be meaningful if the motions of hand are analyzed in terms of the synergy.

2.3 Hand Anthropometry

One of the organism constraints of motor control is physical properties of humans. Humans are not same regarding in their size, proportion or shape of body/body parts, so different individuals show the different result of controlling motion. Anthropometry is a branch of the science that deals with the human body. Section 2.3 describes how anthropometric factors of hand can be defined to investigate the effect on motor control.

2.3.1 Anthropometry in Engineering

The harmony between the operators and the tools they use is an important issue. [55]. According to the dynamic systems theory, hand shape should be considered as a constraint which affects hand motion as mentioned previously. Therefore, in order to fulfill goals, which are enhancing usefulness, safety, fit and comfort, it is required to understand properties of human body prior to engineering or designing artifacts, tasks, systems or even environments. More specifically, sufficient inquiry of body dimensions and capabilities of the potential users should be done [56].

Anthropometry is a branch of the science that deals with the human body, particularly with measurements of body size, shape, strength, mobility, ranges of motion, proportions and flexibility. The anthropometric database generally refers to a set of body dimensions measured on a sample population [55]. As in all other characteristics, humans are various in dimensions, so understanding the variability is inevitable to harmonize humans and tools. For these reasons, anthropometry plays an

important role in ergonomics as well as cognitive and environmental ergonomics and a variety of other sub-disciplines in ergonomics [57]. At the beginning phase of product design, target population and their relevant body dimensions should be identified.

This anthropometric information, human body dimensions, and its segment proportions have been of interest to artists, philosophers, physicians and anatomist and certainly to anyone who designs and provides objects for human use for a very long time [58]. For instance, tomb painters of ancient Egypt who worked in elevation applied a modular grid to their preliminary drawings of the human figures even though they had no perspective [57]. Sculptors of classical antiquity also used a system for their works from which it can be inferred that how they understood human proportion at that time. At the end of the 13th century, Marco Pole recorded a particular interest of the various body sizes and shape that he saw during the travel from Italy to China. Leonardo da Vinci, another well-known researcher, artist, physician, and anatomist, painted 'Vitruvian Man' showing idealized human body and this ratio has been called golden ratio. Around the same time, Albrecht Durer dealt with a real human body and brought scientific beginnings of anthropometry [59].

In the current era, it has become possible to investigate and collect anthropometric data set systemically at the national level with developed technology and increased interest. Many anthropometric surveys such as the CAESAR™ project [60], Size USA, Size China and Size UK have been carried out on civilian populations. Given new demand in the market, access to contemporary anthropometric data for the Korean population becomes more important for designers and manufacturers who

seek to produce the best fitting products and living environments for consumers [61].

For this reason, a national-wide project, called Size Korea project, was carried out in South Korea to collect anthropometric data and to build a database for the Korean population. The national surveys have been conducted every five to seven years since 1979. In the early years, these surveys were conducted with limited people and financial resources, so the result did not meet ISO requirements in terms of accuracy and measurement consistency. However. in 2001 and 2002 the Korean Agency for Technology and Standards under the Ministry of Knowledge and Economy initiated a two-year project aimed at a thorough examination of existing survey data and methods, and subsequently, re-designed measurement techniques and procedures to improve the quality of Korean anthropometric data and to satisfy ISO standards. Now, people can apply the data to design product or workplace and researchers analyze the database to find more valuable application in many industries.

Body dimensions are categorized by type for its convenience of use as follows: heights, circumferences, lengths, depth, breadths, thickness and angles [62]. The definitions of the measurement are in Table 1 [63]. The dimensions can be directly measured using a manual method. Recently, new assessment techniques such as 3-dimensional topography of body surface emerged, and the methods enhance convenience and accuracy of measurements [64].

Measuring anthropometric data is based on bony landmarks as reference points. In anthropometry, landmarks are defined as skeletal points located to the surface of the body, working as the markers which identify the exact location of the measurement

site. For example, length dimensions are achieved by calculating distance between two landmarks. The landmarks can be found by palpation. 3D scanning method which requires landmarks, as well as the direct method, can identify the required landmarks automatically. For all cases, appropriately identified landmarks are the first prerequisite for measuring body dimensions.

2.3.2 Hand anthropometry

Same as body dimensions, hand dimensions can be categorized by type: heights, circumferences, lengths, depth, breadths, thickness and angles. The list of hand dimension and its illustration are shown in Table 2 and Figure 4.

There are some studies on anthropometric analysis which are particularly focused on hand data. Same as of the body, anthropometric characteristics of the hand are varied across race or nationality. Davies [4] conducted an anthropometric study to compare female workers of three ethnic groups, Western Europeans, Indian and West Indian showing significant differences among them. Another study compared hand dimensions of Korean population and the ones of other countries, Turkish, American, Jordanian and Mexican [3].

Besides the comparison between countries or races, the effects of hand anthropometry on the hand function were also examined. Salvendy [65] gave details of hand sizes of British female workers including ten measurements and found the dimensions highly correlated to dexterity. Another researcher collected anthropometry and statistically described the kinematics of human hands and then built the non-invasive prediction model of hand function through external hand data [66].

Table 1. Definitions of body dimension categories

Categories	Definition
Height	A straight-line, point-to-point vertical measurement
Length	A straight-line, point-to-point measurement between landmarks on the body
Breadth	A straight-line, point-to-point horizontal measurement running across the body or a segment
Depth	A straight-line, point-to-point horizontal measurement running fore-aft the body
Circumference	A closed measurement that follows a body contour; hence this measurement is not circular
Thickness (scarfskin)	A thickness of skin for a particular body part
Angle	The slope between a particular body part and reference body part

Table 2. Hand dimensions for each category

Categories	Dimensions
Height	None
Length	Hand length, radial styloid-thumb fingertip length, palm length perpendicular, capitate-finger first crease line length (thumb, index, middle, ring, little finger), thumb-finger first crease line length (index, middle, ring, little finger), finger length (thumb, index, middle, ring, little finger), first phalanx length (thumb, index, middle, ring, little finger), second phalanx length(thumb, index, middle, ring, little finger)
Breadth	Finger breadth distal - thumb, index, middle, ring, little finger, hand breath
Depth	None
Circumference	Hand circumference
Thickness (scarfskin)	Hand thickness
Angle	None

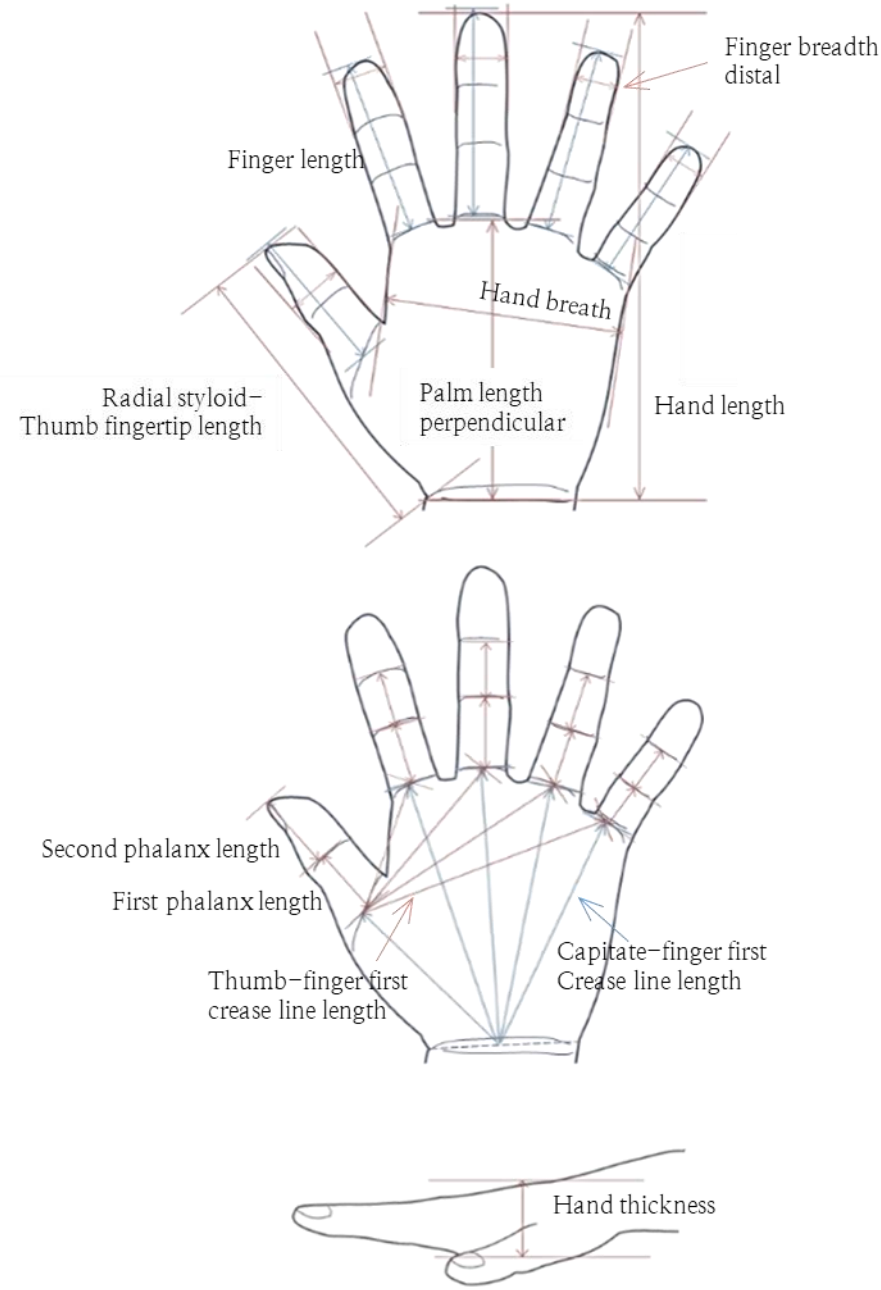


Figure 4. Hand dimensions

According to Garret [67] and Armstrong and Chaffin [68], hand length, and breadth, hand thickness, phalangeal length, digit length, and forearm-hand length are the critical dimensions on hand functions, especially for tool grip tasks. All radio-ulnar, dorso-volar type motions and span are related to the hand grip. The hand can determine the proper size for handheld devices in terms of grip comfort, strength, and preference. Kong and Lowe [69] showed that perceived handle grip comfort was maximized at certain diameters and that the results differed by gender. The results of these studies indicate that the anthropometrical characteristic of hand should be considered in product design to optimize the hand function.

For this reason, some studies explored hand anthropometry for designing a particular product, for example, glove [70], bicycle handle [71], garden tools [16], or a hand tool for the specific occupational purpose. Cakit [72] determined various hand dimensions and biomechanics measurements for dental tools in the Turkish market. The research showed that there was a significant difference between Turkish female dentistry students and other nationalities, and indicated that dental equipment for Turkish dentists should be designed to reflect this difference. However, with the respect of hand-held touchscreen devices, sufficient study has not been conducted considering such hand dimensions.

2.3.3 Hand classification

It is difficult to accommodate the whole user population at once. After dividing the target user population into some meaningful groups, the designer must reflect the unique characteristics of each group in the products. One analytic method to consider anthropometric characteristics when designing or implementing products for practical purposes is to define a representative by clustering body or hand according to the shapes. In the following part of this section, the method used in previous studies will be discussed.

There are numerous researches to define body shapes which represent a target segment. Most studies had a specific purpose in classifying body and many of them are related to classifying the type of whole body [73–75]. For practical purposes, some studies focused on specific parts of the body such as the upper/lower body or torso.

Human hands were the other body parts to be classified. There is a large variation in hand anthropometry over the population. However, hand tool designers sometimes assume "one size fits all" [66]. Handles and controls of hand tools need to be designed for both efficient and safe use by considering the large variation. Many studies inquired the relationship between hand size and grasp power. Some studies, such as those by Pheasant and Scriven [76] and Härkönen [77], concluded that the size of hand alone did not affect grasp power. On the other hand, other studies concluded that the interaction between handle size/shape and the kinematics/anthropometry of the hand have a significant effect on grip posture and strength. Eksioglu [78] and Oh [79] both concluded that the optimum grip span depended on the size of users' hands in their

own researches. Due to its disagreement, researches on the effect of hand size as well as other hand dimensions should be continued.

As one approach to finding the effect of hand anthropometry, some studies have classified hand type for various purpose. According to Jee [3], the Korean population was classified into four clusters expecting the results to be used as baseline data to design and develop hand tools. Another study classified hands of the same population into two clusters but used different data set including 58 hand dimensions from 325 subjects [80]. Besides the Korean population, hand data of USA army reported in 1988 were divided into three groups with hand length and circumference as key factors for determining bicycle handle diameters [71]. In another study assigning participants into three hand size groups by hand lengths, Jung [81] found the effects of user's hand size on operational ability such as maximum grip strength and individual finger force as well as subjective comfort rate.

Compared to the body, fewer researches/applications have been conducted on the hand. Also, since the studies had particular purposes for classification, such as designing glove or hand tools, it is difficult to apply the results to other purposes, for example, understanding the use of smartphone which is not same as other hand tools.

2.4 Human Grasp Taxonomy

One main function of hand is grasping with an opposable thumb. The performance of human grasping is far more outstanding and dexterous than one of other primate or even robot hand. Taxonomies of grasp were developed by several researchers for applications including grasp recognition, robot hand design and interaction design which requires more sensitive grasp. This section describes what the existing taxonomies of grasp are and how the grasp is defined.

2.4.1 Existing studies on human grasp taxonomy

Humans use the hand mostly for grasping beyond any type of manipulation. Through grasp, the hand can keep stability during performing tasks or operating an object. For successful use of objects, human choose or modify their grasp appropriately.

There is some source of constraints in grasping [82, 83]. Among them, functional and physical constraints work as criteria for establishing taxonomy. A functional constraint is a property that indicates how the object will be grasped during task performance. An example of a fundamental functional constraint is the purpose of grasp which is not to drop the objects; this indicates that the main goal of the prehensile task is to maintain a stable grasp. Another functional constraint is inevitable instability when the object is manipulated by transferring a certain amount of force to the object or transporting the object. Human hands react to this instability by modifying their grasp posture.

Physical constraint includes external forces such as gravity and friction, and anthropometrical properties of hand as well as physical properties of the object. Anthropometrical factors such as hand/finger length and range of motion (ROM), of course, can limit the hand posture during grasping. The grasp posture which includes the location and orientation of the hand or the number of fingers contacting the surface of the object is determined by the physical properties of an object, for example, size, shape, texture and weight.

There is another perspective of defining grasp constraints: task, object or the gripper constraints as illustrated in Figure 5. There are three overlapping sets of constraints from the task, the grasped object and the grasping hand. The task constraints include forces and motions required. The shape and friction on the surface of the object are the examples of the object constraints. The constraints arising from hand can be the required grasp force and range of motion of the fingers.

Again, grasp postures are determined by a hand tool design and the purpose of the hand tool use. For example, among various postures, people grip cylinder type handle allocating their thumb on the same plane of the palm, adducting the MCP and CMC joints and flexing fingers if the task requires some amount of potent force. When it comes to fine control such as rotation and complex manipulation, it is suggested to grasp the handle in the opposition between the thumb and finger pads.

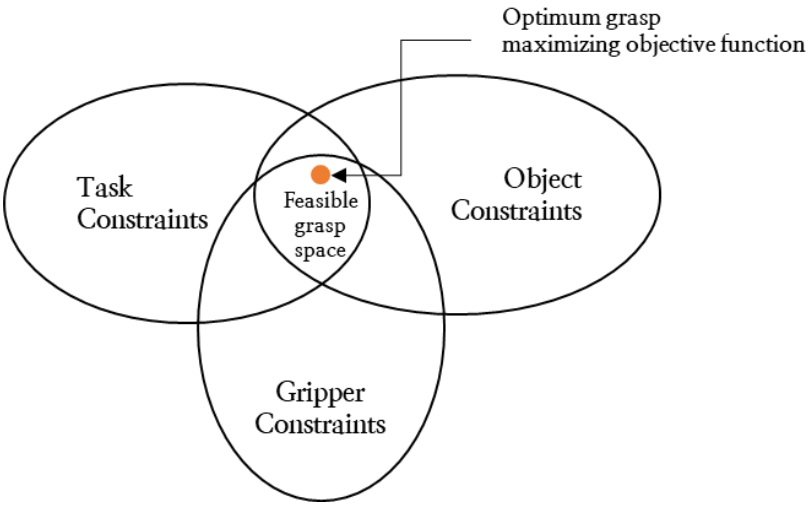


Figure 5. Feasible grasp space and optimum grasp according to the objective function to task, object and operator constraints [83]

Considering this purpose, many studies have made a noticeable effort to establish grasp taxonomy for various reasons with different perspectives in medical, clinical, occupational and industrial applications. In the previous researches, grasp has been classified according to characteristics of task or object. Schlesinger was the person who made the first major attempt to construct human grasp behavior in distinct categories such as cylindrical (open- and close-fisted), tip, hook, palm, spherical and contour grasps [82]. These grasps were mainly defined by the objects interacting with the hand. In addition to the grasping object, the task is also the determinant of grasp selection. The classifications of Napier [84] included power grip which requires stability and security, a precision grip which requires sensitivity and dexterity, and combined grip in which radial fingers positioned for precision grip and ulnar fingers for power. Considering the characteristics of the object, the power and precision grips were divided into nine sub-categories and seven sub-categories, respectively, by Cutkosky and Howe [83]. Other grip postures include the lateral pinch in which the object is held between the thumb pads and the radial side of the index finger (e.g. spinning a key) and dynamic grasp that interacts with an object using fingers to grasp allowing dynamic behavior (e. g. writing with a pencil). Later, more diverse types of grasps were defined and classified. Prehensile classifications have been developed for daily life tasks including those of Kapandji as cited by Mackenze [82], Elliott and Connolly [85] and Kamakura et al. [86]. For example, Kamakura [86] divided grasp patterns of normal hands into 14 patterns under four categories, which were power grip, intermediate grip, precision grip and grip involving no thumb action. They also showed the detailed contact area of the hand in the case of each grasp pattern and confirmed 98 objects and their corresponding categories. Some studies had attempted

to figure out the grasp more focused on everyday products. Zheng et al.[87] adopted this taxonomy to analyze the daily activities of experienced a machinist and a housemaid. They counted the number how frequently the subject uses different grasps. A similar study was conducted by Liu, Feng, Nakamura and Pollard[88]. They considered a broader range of actions besides static grasping focusing on the differences observed in grasps which have the same entries in the classification. The grasp taxonomies established by various researchers are listed in appendix A.

Among those existing grasp classifications, the most widely referenced prehensile classification in anthropology, medicine, biomechanics, and robotics is that of Cutkosky [83], which includes 16 grasp patterns adopted in skilled machining tasks. Cutkosky's taxonomy contains a hierarchical tree of grasps which classified prehensile patterns regarding power and precision. When researching the grasp of manufacturing work, Cutkosky provided a comprehensive and detailed human grasp organization. This taxonomy was collected through a series of observations on professional mechanics and incorporates the previous work by Schlesinger and Napier. The Cutkosky taxonomy tree is organized first by force and precise grasp, and then, by tree shape and function. This taxonomy was originally applied to robotics, which has been proven to be suitable for transferring human hand-held movements into a robot hand. Although the classification was made for robotic applications, this plan is sufficiently comprehensive to account for human identification [6].

Another comprehensive taxonomy of grasps was developed by putting previous researches together by Feix [89]. By reviewing 17 papers, they found 147 grasp

examples. Out of 147 examples, 45 distinguished grasp types were detected. According to the definition of grasp. Feix and his college defined a grasp as follows: "A grasp is every static hand posture with which an object can be held securely with one hand." According to this definition, total 33 grasp types were generated, excluding two-handed tasks, intrinsic movements, gravity-dependent grasping and flat hand grasp. The category was extended by adding an intermediate grasp to power and grasp precision, and each category had two components of grasps, thumb abduction and adduction.

In classifying the grasps, the thumb is distinguished from other fingers because the thumb motion is known to be the most critical to the grasp of all five fingers. Radial abduction, adduction and opposition of the thumb were all related to the grasp posture and strength [65].

The category of smartphone grasp is not robustly defined in the current classification; few studies were conducted for focusing smartphone grasp. Kim [90] defined eight grip patterns for smartphone use according to tasks: call, SMS(single handed), SMS (two-handed), horizontal camera, vertical camera(front and rare), video and game. However, this study did not provide any connection to the existing taxonomy. Recently, Lee [23] attempted to find grasp for smartphone by matching previously defined grasps in his research. Smartphone grip postures also vary according to tasks or smartphone applications and require a proper combination of power and precision to hold the device and achieve the intended interactions, resembling dynamic grips. Together with the previous work, the grasp of the hand-held touchscreen device for one-handed operation involved five types of grasp

differing by the contact regions between the glabrous hand skin and the device, the involved fingers and the power- or precision-oriented nature. However, in this research, thumb operations were not considered. Therefore, it should be useful to inquire grasping hand-held touchscreen devices and compare to the existing grasp taxonomies.

2.4.2 Methodologies to identify human grasp

In some researches, the hand grasping has been viewed from an aspect of muscular synergy or muscle synergy. Muscular synergy is defined as a coordinated activation or pattern of some groups of muscles [51, 91]. Previous studies factorized EMG signals to represent hand posture during grasping [52] and found a correlation between the muscles to identify muscle use patterns such as co-activation or trade-off relationship. The fewer factors or components achieved by PCA could encounter a greater number of muscles maintaining the original information. Through this analysis, it was possible to explain muscle recruitment patterns during grasping, to conduct an analysis much easier, and to visualize the result more intuitively.

The other method focused on finding a functional link between biomechanical architecture and hand posture in terms of joint angle. The studies were mainly worked on bare-hand interactions [92, 93], sign language or hand gesture recognition [94, 95], prosthetic hands [96] and robotics [97, 98]. The researchers compared the movement-coordinated relationships between joints of the human hand during various grasps, for example, medium wrap, power sphere, tripod, lateral, precision disk and index finger extension type. One study analyzed smartphone use

through joint angles of fingers with the purpose of user authentication when performing tasks including multi-touch interactions, but this did not consider grasping.

Joints involved in all-natural motor activities are controlled by the net torque generated by muscle activities on those joints. To identify muscle coordination or its strategy, a set of muscles which can represent all key muscles of the motor behavior need to be connected to corresponding patterns of joint angles. For this reason, some studies brought EMG data and joint angle recordings together. In this dissertation, EMG signal and joint angle will be recorded simultaneously and factorized as muscular and postural synergies. These synergies will be used to define grasp taxonomy including the smartphone.

2.5 Touch Screen Interactions

As mentioned before, smartphone grasp is not robustly defined in the current taxonomies. To allocate the hand-held touchscreen grasp appropriately, it is necessary to analyze it. Section 2.5 introduces previous studies for the device to review findings and limitations and based on the materials from the review, experiments will be designed and analyzed.

2.5.1 Previous studies on a mobile phone

Button-type mobile phones were used before the development of touch-screen smartphones. Since the public has used the button type phones for decades, many studies have been done on form factors, for example, button layout, size, shape or required force to operate the device. For instance, Hogg [27] reported that greater effort was perceived for the thumb when using the keypad in the right bottom corner of a mobile phone. However, the thumb movements on a hand-held touchscreen device may be significantly different from those on the mobile phone with a tactile keypad; the main mode of operation of traditional mobile phones has been replaced by lightly tapping the flat touchscreen surface from pressing a button. Thus, it remains questionable whether or not the results from the old type mobile phone match those for a hand-held touch screen device. Therefore, although there are many studies on mobile phones, the change of interaction requires research on touch screen devices. Researchers should not apply the results of an outdated phone without validation.

For this reason, researchers have reported issues related to the hand-held touchscreen device use such as the possible association between musculoskeletal disorders and the device [30], the effect of age on smartphone use[24], the performance of touch interaction and usability [29, 99]. Recently, Lee [100] investigated grip comfort, postures, index finger reach areas and muscle activations associated with different hand sizes, device widths, and tasks during index finger interactions on the rear areas of smartphone mock-ups. As a result, it has been demonstrated that hand size needs to be considered when determining smartphone size, but it is not clear how hand size will affect the device usage so far.

2.5.2 Thumb performances studies

The thumb contributes approximately 40% of hand functions as mentioned above. Due to this considerable contribution, many studies have inquired thumb operation related to the hand-held touchscreen devices. Xiong and Muraki [25] insisted that "the thumb greatly affects, even determines, the input performance on the touch screen of smartphone" in their paper. The thumb is the only finger that can manipulate the devices, so the muscle activities of the thumb are ideal indicators for assessing musculoskeletal loads of mobile phone use [26]. They inquired thumb reach area, which was also called thumb envelope or coverage area, degrees of freedom, performance including movement speed and accuracy (or called offset). Trudeau and his colleagues [22] suggested that thumb movement in adduction – adduction is faster than in flexion-extension orientation based on thumb motor performance and joint coordination, and thumb muscle effort was barely involved in their study. In another study, it was concluded that those who had shorter thumbs needed to ensure that the

phone was close to the thumb due to the limited thumb length in order to cooperate with other fingers to retain the phone in the hand. The limited length of thumb also limited the transaction that stabilizes the MCP joint, which markedly reduced the extension movement of the thumb [101, 102]. In contrast, longer thumbs were likely to have larger hands, they tend to have greater freedom to grasp the device, which allowed the thumb to reach higher on the screen, thereby covering a larger thumb reaching the area.

Despite numerous studies done on thumb operations, much fewer studies have focused on grasping alone or together with thumb operations of the device. A study attempted to explore hand grasp during smartphone use considering several tasks or interaction methods. However, a grasp was defined as the preferred contact points of the fingers on the back of the device in the study, and this result did not explain details of the smartphone grasp. Although the previous works have provided a categorization of grip styles for other hand tools, a detailed understanding of the preferred postures of fingers is missing during manual tasks for the device.

2.5.3 Interaction types and levels

As touch interface has been the major interaction method for hand-held touchscreen devices, many studies have conducted on various types of them. A study conducted by Cho [103] defined tap, move and flick as the main interaction methods. Tap, as the basic touch interface, was defined as hitting a surface lightly with the fingertips. Utilizing move interface, by its definition, an object was changed to a different location having initial and end points. It is also able to track trace of the

movement. Flick, in the same study, was defined as fast scrolling either horizontal or vertical list of items on the screen and contained neither initial points nor end points targeted by the user. In other words, this interaction can be used when the user does not have any intended points. Due to this property, the flick is hard to be controlled during an experiment. Typing can be basically defined as a series of taps. However, during uni-manual operations, typing keyboard is not suggested. A special case of typing, called gesture typing, was suggested to solve this difficulty. This method differs to a common typing interface since this is not allowed to detach a finger until typing finishes. Instead of discrete tapping, this is almost like a line drawing [104]. Through this interaction, the system can recognize words that the user intends to type and this method allows smooth motions which human tend to maximize in their movements [105]. Despite its advantages, this method is rarely used by users. In this dissertation, the simplest interactions, tapping and dragging, which could be completed by a single hand will be selected for the experiment.

2.5.4 Experimental Design

Setting task levels of the touchscreen device

Previous studies sectioned the entire screen of the device to find the appropriate location of buttons. For example, the thumb envelope where users' thumb could reach without re-grasping was defined to investigate the user characteristics that affect the thumb envelope area [24, 106]. In other studies, the screen was divided into several areas according to comfort level [107], and the screens were divided at regular intervals [108]. Many studies divided the screen meaningfully, according to the

purpose. Once the screen is divided into subsections, a target for tapping can be allocated.

In most cases, drag interaction normally includes four or eight directions. Due to the natural thumb alignment, it is better to include oblique directions for the dragging, so eight directions are considered appropriate.

Measure

Most of the previous studies measured EMG data. One study found that people enter text on mobile phones with tactile keyboards by one thumb rather than two hands, and higher muscle activities were detected in the muscle APL of the thumb when typing with a faster speed [109]. Jonsson [110] pointed out that the muscle activity of the thumb is an ideal indicator for assessing musculoskeletal loads of mobile phone use. However, this is not enough to understand smartphone usage comprehensively.

Some studies collected EMG data together with joint angles as mentioned in Section 4.2; rather than simply holding gesture, some studies in neuroscience, neurobiology, robotics or mechanics analyze hand motion in the aspect of muscular or postural synergies. However, this method has been rarely used in human factors or ergonomics field. Also, the studies to analyze hand grasping using synergies were not targeted touchscreen smartphone. The muscle synergy and postural synergy obtained by respectively combining EMG and joint angles will be defined and used to analyze hand motions in this dissertation.

Chapter 3. Anthropometrical Analysis on Hand

As mentioned previously, it is useful to classify human hands for a specific purpose in general cases. Regarding the handheld touchscreen devices, such as a smartphone, researches dealing with the hand classification to investigate usage behavior for the device have been rarely done yet. One study investigated the effect of hand size on smartphone use was very recently completed, but the hands were classified based on hand length only [23, 100]. However, the previous study suggested that the hand shape acts differently to smartphone use pattern [106].

The previous studies for hand classification, also, did not provide strong evidence for the selected clustering methods. Normally, partitional clustering, in particular, k-means clustering or hierarchical clustering methods were performed for classification of a body including hand, but those methods may not be appropriate for this research.

This chapter will cover the most appropriate hand classification for smartphone use by focusing on performing cluster analysis properly, from selecting and extracting data from collected data achieved by Size Korea, finding most appropriate clustering result by comparing several clustering methods and interpreting the meaning of the result. The result will be the base of the further part of this dissertation.

3.1 Hand Type Classification Method

3.1.1 Clustering methods in general

Clustering, or cluster analysis, is for partitioning data into a certain number of clusters. Clustering methods can be divided into different categories; generally, hierarchical clustering, partitioning clustering, and model-based clustering.

In the hierarchical clustering, a hierarchy of cluster is produced with a given data set. A criterion for distinguishing types of this method is the direction of building hierarchy; one is agglomerative (bottom up) and the other is divisive (top-down) clustering. In the agglomerative hierarchical clustering, each case starts in its own cluster, and pairs of clusters are merged as one moves up the hierarchy. On the other hand, in the divisive approach, all cases belong to a single cluster and start to split recursively as one moves down the hierarchy.

The partitioning method is used to group cases within a data set into multiple groups based on their similarity. This method can be divided into hard clustering and soft clustering. The hard clustering offers a result that each object belongs to a cluster or not. On the other hand, the soft clustering which is sometimes called fuzzy clustering is a method in which each object belongs to each cluster to a certain degree, for example, a likelihood of belonging to the cluster.

The model-based clustering assumes that the data is generated by a model, often a mixture of multivariate normal distributions, and tries to recover the original model from the data. Each component is described by a density function and has an

associated probability or weight in the mixture. In this method, the component in the mixture is defined as a cluster.

The procedure of cluster analysis mainly consists of four steps. Figure 6 describes the process. Data works as input and clusters and the knowledge are the outputs of clustering algorithm design/extraction and result of the interpretation stages of the analysis, respectively. At each stage, the researcher can go back to the previous stage anytime if it is necessary.

Feature selection or extraction

Feature selection refers to selecting distinguished features from a candidate data set, and 'feature extraction' does to transferring original features to appropriate form. The outcome of the feature selection/extraction phase should be the appropriate features to represent the input data with a reduced number or redundant [111]. The researchers can use a raw data set which is related to cluster hand types as input, if and only if the data contains an acceptable number of body dimensions. However, if there are too many variables, feature extraction is required by reducing the number of dimensions. In this case, techniques of feature selection and extraction can be applied.

Feature extraction is likely to generate better features of uncovering data structure, but it may not be easily interpreted. On the other hand, feature selection is able to offer features without distorting original information. Both are highly influential to clustering applications, so they can greatly decrease storage and clustering cost, simplify algorithm design leading to enhancing understanding of the result.

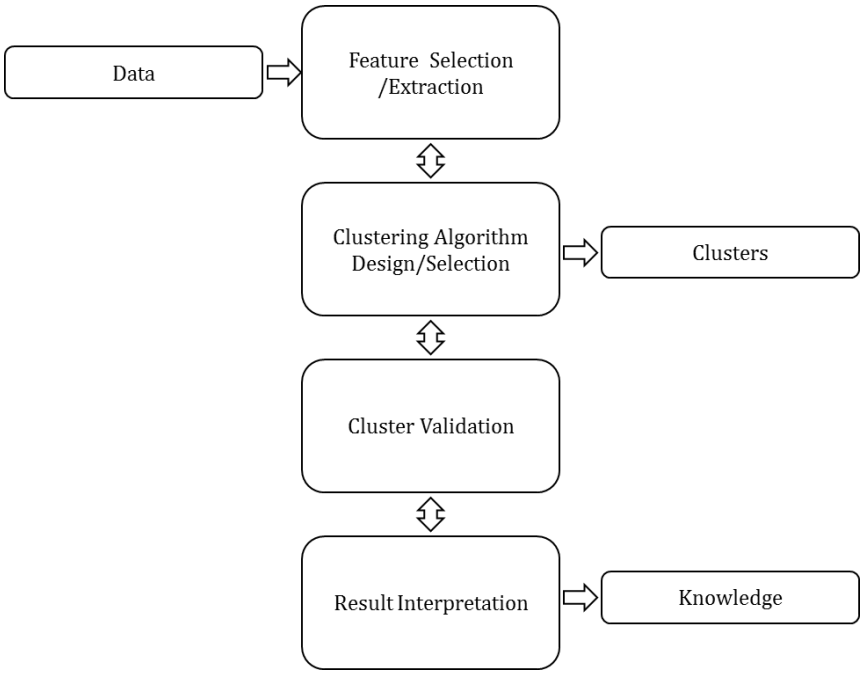


Figure 6. The procedure of clustering [112]

Principal component analysis (PCA) is one of the most useful dimension extraction techniques. PCA is a statistical technique that linearly transforms an original set of variables into a substantially smaller set of uncorrelated new variables that represents most of the information; the goal of PCA is to reduce the dimensionality of the original data set. A smaller set of the new variables, which is called principal components, is much easier to understand and to use in further analysis than a larger set with correlated variables. The idea is originally conceived by Pearson and independently developed by Hotelling [113]. PCA can be modeled as $C = YB$, where Y is a matrix of observed variables, C is a matrix of scores on components and W is a matrix of eigenvectors or weights.

Factor Analysis (FA) is another way to extract features or dimensions. In the FA, observed variables are modeled as linear combinations of potential factors and "error" terms. Factor analysis assumes that for a collection of observed variables, a set of elemental common variables, called factors, exist with a smaller number than the numbers of observed variables. These factors can also explain the interrelationships among the observed variables. FA is modeled as $Y = X\beta + E$, where Y is a matrix of measured variables, X is a matrix of common factors, β is a matrix of weights (factor loadings) and E is a matrix of unique factors, error variation. Figure 7 and Figure 8 describe the scheme of PCA and FA.

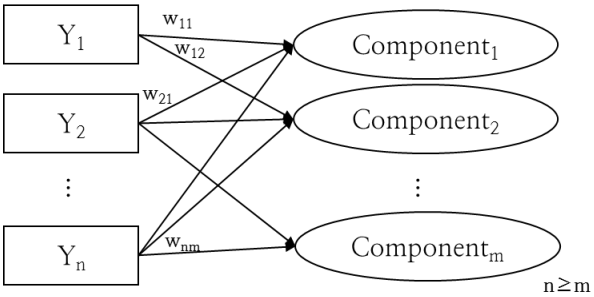


Figure 7. Schema of principal component analysis

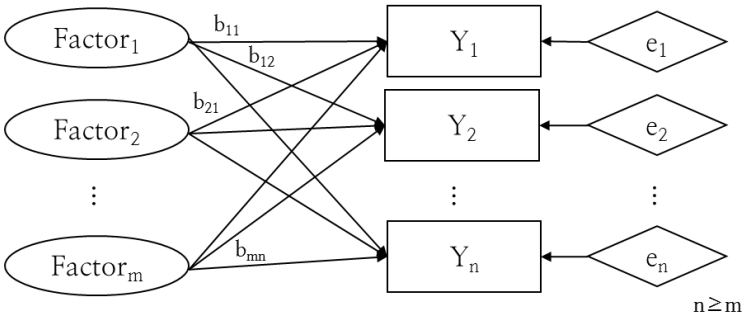


Figure 8. Schema of factor analysis

The PCA and FA are feature extraction methods mostly used before body clustering. Results from cluster analysis often differ according to the feature extraction or selection methods. PCA is often used to approximate sub-dimensional data when the sum of the square of the approximation error is small. Factor analysis is also used to approximate sub-dimensional data and the measurement error is independent. However, the projection of factor scores is debatable. Moreover, there are ways to select key components in order, but factor analysis defines only the k-dimensional subspace.

In the statistical point of view, each method has pros and cons. If researchers do not assume any specific underlying model of the data, for example, when visualizing the clustering observations, the PCA can be applied to establish the structure of a data set. The PCA can also be used as an adjunct to multivariate analysis procedures such as regression analysis to solve the problem of multicollinearity. On the other hand, factor analysis has a decided advantage over PCA if the variables contain a substantial amount of measurement error, which researches in the behavioral and social sciences field may often have or if an underlying factor model for the data is assumed. The common factors are uncontaminated by measurement error because the error is part of the unique variance which is uncorrelated with the common variance [114]. In the case that the communality of the variables is high or there are a large number of variables, it is known that both PCA and FA will give similar results.

In a study comparing the results from two cluster analysis using features achieved by PCA and FA to each other, it was concluded that the results were not same [115]. For this reason, researchers should carefully select the feature extraction method to

consider characteristic of data.

Clustering algorithm design or selection

This phase usually consists of determining an appropriate proximity measure and constructing a criterion function. Almost all clustering algorithms are explicitly or implicitly related to one or more particular proximity measures. Once a proximity measure is determined, clustering could be construed as an optimization problem with a specific criterion function. Results of cluster analysis are dependent on the selection of the criterion function, so the analysis involves inescapable subjectivity.

Cluster analysis can be classified into partitional and hierarchical or hard and soft as mentioned previously. Each clustering method has various types. Many clustering algorithms have been developed to solve different problems from various fields. However, no algorithm is universal to solve all kinds of problems. It is important to find the characteristics of data set to apply an appropriate clustering algorithm and make reasonable assumptions.

Hard classification. Most studies conducted a k-means algorithm among hard clustering, but the method has limitations. The k-means is a well-known clustering algorithm that partitions a given dataset into k clusters. It needs a parameter k representing the number of clusters which should be known beforehand or determined as a fixed apriori value before going to cluster analysis. The k-means clustering is reported as a fast, robust and simple method to implement in most cases. As reported in many other studies, however, it gives comparatively good results if clusters in datasets are distinct or well separated. It was also examined that the k-

means method is relatively efficient in computational time complexity. Despite its advantages mentioned above, k-means clustering has several disadvantages regarding the form and scattering of clusters in datasets. First of all, k-means may not be successful to find overlapping clusters, and it is not invariant to non-linear transformations of data. For that reason, representations of a certain dataset with Cartesian coordinates and polar coordinates may give different clustering results. The k-means also fails to cluster noisy data and non-linear datasets.

Fuzzy classification. A well-known algorithm of fuzzy cluster algorithm is c-means. In order to solve the problems of the k-means clustering, Bexek [116] suggested Fuzzy c-means (FCM) as an extension of the k-means clustering, based on Dunn's study [117]. Many studies such as the works done by Suganya and Shanthi [118] and Ali et al. [119] had great effort to develop the algorithms to improve the efficiency and accuracy of the FCM. Nonetheless, the basic FCM algorithm has been widely used to applications from engineering to economics. An object does not belong to a single cluster and it is allowed to be a member of many clusters in varying degree of membership between 0 and 1 as well. In this way, objects located near boundaries of clusters can belong to various clusters reflecting affiliation to its degree of membership. In spite of higher complexity compared to k-means clustering, the FCM has been used in many academic and practical areas due to its advantages [120, 121].

Although FCM is believed to be more efficient to analyze fuzzy data, it does not always have superiority in all cases [122-125]. Thus, it would be helpful to examine these hard and soft clustering algorithms for the data structures according to research purpose.

Model-based clustering. Latent profile analysis (LPA) is a specific case of a Finite Mixture Model (FMM). It is similar to k-means and fuzzy c-means algorithms in the aspect of determining the number of classes that is determined through the comparison of posterior fit statistics. FMM and other clustering algorithms show the difference that the former offers the "model-based clustering" approach which derives clusters using a probabilistic model that describes the distribution of data. Same as this, LPA assumes the distribution of clusters and attempts to estimate the likelihood of each variable for each cluster. Instead of finding clusters with an arbitrarily chosen distance measure, a model that describes the distribution of a given data can be used. Based on this model, researchers assess probabilities that certain cases are members of certain latent classes. Therefore, it is a top-down approach in which an analysis starts with describing the distribution of given data, while other clustering algorithms are rather bottom-up approaches which find similarities between cases.

For example, since the k-means algorithm is performed based on the Euclidean distance, hyper-spherical clusters tend to be generated. If the actual cluster has other geometric forms, the k-means may no longer be valid. It is necessary to pay attention to similar considerations to mixed model clustering in which it is assumed that the data comes out of a specific distribution already known in advance [112].

Some studies just set criteria for each dimension, component or factor, and others conducted soft clusterings such as fuzzy c-means or SOM. In other fields, recently, latent class analysis or latent probability analysis has been applied.

Cluster Validation

Once a clustering analysis is performed with a given data set, it produces a partition whether or not it really has a particular structure. The accuracy of clustering algorithm results is examined by appropriate standards and techniques. Because clustering algorithms as unsupervised method generate clusters that are not known a priori, regardless of the clustering method, the final partition of the data requires some sort of evaluation in most applications. As mentioned previously, various clustering approach can generate different results and using even the same algorithms, the result can be different according to the features or parameters selected. As unsupervised methods, cluster analysis requires rigid and effective evaluation to provide researchers with a sufficient level of confidence. The evaluation criteria should be algorithm-independent and objective [126].

There are two measurement criteria proposed for evaluating clustering scheme, compactness and separation. The definition of the two terms is as follows.

- Compactness: The members which belong to the same cluster should be as close to each other as possible. Compactness is commonly measured by the variance.

- Separation: The clusters must be widely separated as far as possible from each other. There are three general ways to measure the distance between two different clusters: 1) distance between the closest member of the clusters, 2) distance between the most distant members and 3) distance between the centers of the clusters.

By their definition, it can be inferred that compactness should be minimized and separation should be maximized to get the best result.

In general, it is known that there are three categories of cluster validity measurement: external criteria, internal criteria and relative criteria. The first two criteria, internal and external criteria, are based on statistical methods and are highly computationally demanding. The external validation method evaluates clustering based on a predefined structure reflected by prior information about the data. Internal criteria are based on data sets and clustering algorithms and do not rely on prior knowledge. The main disadvantage of these two methods is the computational complexity. The basis of relative criteria is another clustering schema comparison. One or more clustering algorithms run multiple times with different input parameters in the same dataset. The goal of relative criteria is to select the best clustering algorithm from different outcomes. The basis of comparison is the efficiency index. Some effect indices have been developed and are being introduced.

This is related to the inherent features of the data set under concern. The majority of algorithms are based on certain criteria in order to define the clusters in which a data set can be partitioned. Since clustering is an unsupervised method and there is no apriori indication for the actual number of clusters presented in a data set, clustering results validation is required.

Result interpretation

The purpose of clustering is to acquire meaningful insight from categorizing data set into different classes and to assure that the objects belonging to the same class are

similar each other and those belonging to different classes are not. The result from clustering analysis should be interpreted by integrating other experimental information and domain knowledge to fully understand the data. Furthermore, they conduct more analysis; cluster analysis is not a one-time process.

3.1.2 Hand clustering for this study

This section aims to determine the operational motion of a hand during smartphone use. At first, feature selection and extraction will be appropriately done for the purpose of this study. Then, the clustering algorithm will be selected properly; existing studies mainly used the k-means clustering without sufficient explanations, but comparing several other clustering algorithms is required through the cluster validation index for hand classification.

The data set is achieved from SizeKorea. This contains hand related dimensions of 314 people, aged from 20 to 83. The original data contains 61 hand dimensions.

Feature selection

Among 61 hand dimensions, 34 hand dimensions were considered operation-related dimensions and selected as input. The selected dimensions are illustrated in Figure 9. Those were a circumference, width, and depth of a hand, the length and width of a palm, proximal part of fingers and the length of joints and fingers. Cases which had missing data were eliminated from the input data set. The dimensions and their descriptive statistics are shown in Table 3.

Generally, body dimensions can be slanted due to a few extreme cases or normally

distributed. This is examined by skewness which indicates the amount and direction of departure from horizontal symmetry. Another term, kurtosis, is which explains how tall and sharp the central peak is, compared to a normal distribution. These two terms can test normality. Breadth dimensions for fingers tended not to be skewed but showed flatter distribution than the normal distribution. Same as breadth, length dimensions of fingers had flatter distributions. Depth dimension of hand, hand depth, showed a positively skewed distribution with peak. The finger's breadth was rarely skewed and comparatively uniformly distributed. Length dimensions were positively skewed and flat; only radial styloid-thumb fingertip length kept symmetry.

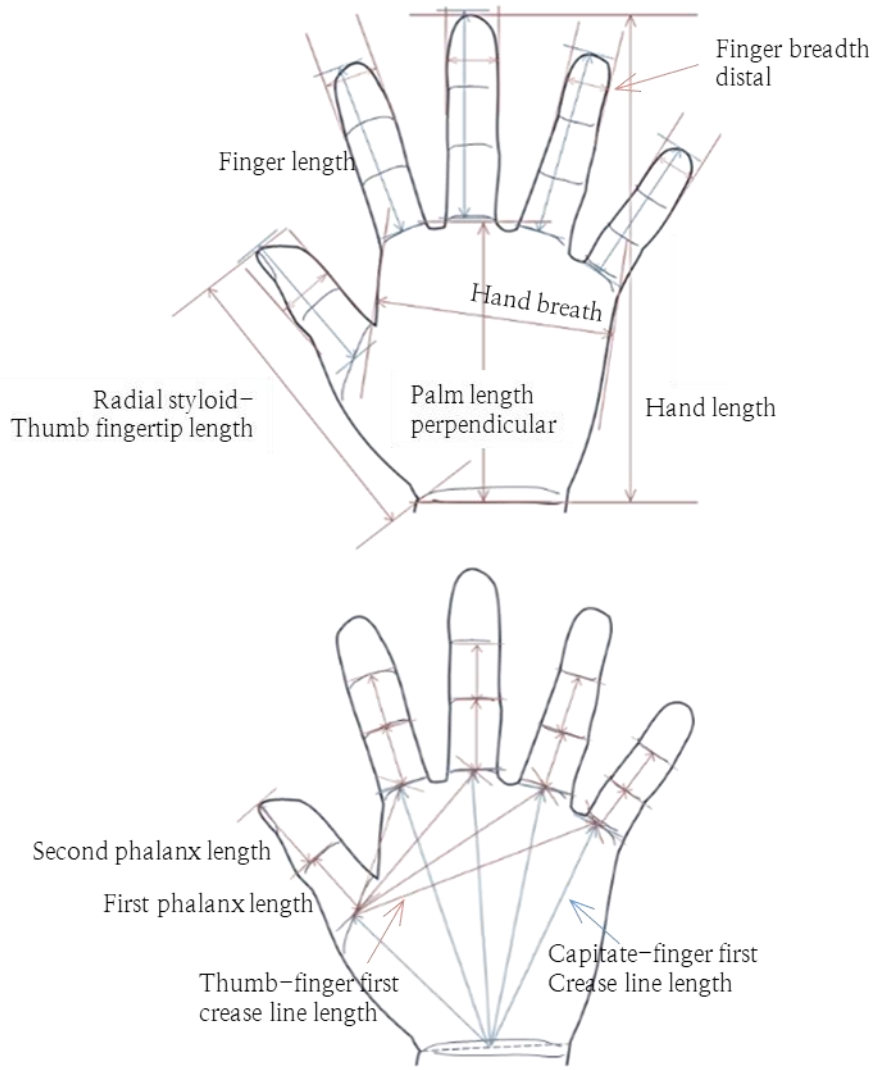


Figure 9. 34 hand dimensions selected

Table 3. Average and standard deviation of hand dimensions (in mm)

Hand dimension	Average	Standard deviation
Finger breadth distal - Thumb	21.12	2.05
Finger breadth distal – Index	17.15	1.54
Finger breadth distal – Middle	17.27	1.56
Finger breadth distal – Ring	15.93	1.50
Finger breadth distal - Little	14.57	1.51
Hand breadth	82.19	5.61
Hand thickness	26.22	2.42
Hand Length	177.27	10.19
Radial styloid-thumb fingertip length	114.52	7.58
Palm length perpendicular	101.33	6.02
Capitate-Finger first crease line length - Thumb	76.55	5.46
Capitate-Finger first crease line length - Index	109.12	6.58
Capitate-Finger first crease line length – Middle	108.79	6.62
Capitate-Finger first crease line length – Ring	104.12	6.71
Capitate-Finger first crease line length - Little	95.76	6.45
Thumb-finger first crease line length - Index	51.28	6.02
Thumb-finger first crease line length – Middle	65.59	6.72
Thumb-finger first crease line length – Ring	75.55	7.11
Thumb-finger first crease line length – Little	85.73	7.31
Thumb length	58.87	4.54
Index finger length	68.47	4.70
Middle finger length	76.16	4.96
Ring finger length	71.81	5.07
Little finger length	56.96	4.92
First phalanx length – Thumb	28.42	3.30
First phalanx length – Index	22.96	2.20
First phalanx length – Middle	25.98	2.36
First phalanx length – Ring	23.19	2.31
First phalanx length - Little	17.67	2.18
Second phalanx length – Thumb	32.21	2.63
Second phalanx length – Index	20.76	2.21
Second phalanx length – Middle	24.23	2.31
Second phalanx length – Ring	22.37	2.22
Second phalanx length - Little	15.39	2.22

Feature extraction

As mentioned previously, the PCA and FA are two common feature extraction methods prior to performing clustering, and they have similarities and differences. The PCA analyzes all variance of the data set, while the FA analyzes only common variances, so results from cluster analysis depend on the feature extraction method. Therefore, finding an appropriate method is required and should not be abused. A priori decision on the feature extraction often depends on the domain expertise, and the statistic characteristics of the data set. Many of the existing studies related to hand shape clustering did not contain any explanation to choose the PCA or FA. More tended to adopt the FA [3, 80] than the PCA [71].

The dataset used in this research, the hand dimensions were highly correlated. Also, there is no specific model for hand dimensions. Considering this together with the recent movement of use of FA toward confirmatory factor analysis rather than exploratory factor analysis [113], PCA was applied in this study.

Clustering algorithm: k-means, fuzzy c-means and LPA

In most cases of the body and hand classification, the k-means clustering has been performed. However, there are some limitations to this approach. The k-means algorithm is based on the Euclidean measure and hence tends to generate hyperspherical clusters. However, if the actual clusters are in different geometric forms, k-means may be no longer effective.

Most cluster analysis approaches offer clustering results based on distances between variables minimizing compactness or within-cluster differences and

maximizing separation or between-cluster differences [127, 128] rather than objective fit criteria. Such approaches make researchers judge subjectively, and due to lack of objective criteria, bias occurs in determining the number of the clusters. In their review of cluster analysis, Ketchen and Shook [127] warned that cluster analysis is likely to be atheoretical and to generate not very meaningful clusters if it is abused. The subjectivity may reflect the results toward supporting the author's intention and bring inaccurate sub-divided groups.

In addition to this, the main difference between k-means/fuzzy c-means and LPA is that the former only detects spherical clusters, while the latter can adjust itself to an elliptical cluster. It means that LPA mitigates the restriction that all clusters have the same shape. Due to this property, LPA has strength in defining human body shape types which have their own distribution. Some cases of latent class models are called "nonparametric" which means that the distributions of the latent variables are not assumed and that there exist parameters to estimate. The selected hand dimensions were not normally distributed as mentioned above. Thus, it would be helpful to examine and compare the results of the k-means, fuzzy c-means and LPA method for the hand data set.

Cluster Validation

In this section, two validations were performed. First, the results derived from the three clustering methods were compared to each other by external validity index. Secondly, to evaluate the best or most appropriate clustering algorithm, related validation was applied to each method.

Through PCA, components could reduce its number reflecting the original variance of the data. Based on component scores, the three types of cluster analysis were performed. To decide the number of clusters, some validation techniques were utilized; Calinski-Harabasz (CH) index was the criterion for determining the number of clusters by k-means and fuzzy c-means, and Bayesian information criterion (BIC) was for model selection among a finite set of models achieved by LPA. At the last, the results acquired from three clustering methods were compared by using the adjusted Rand index (ARI), one of external validation index.

Result Interpretation

The clustering result was interpreted to obtain the answer to the question of how many different types of hands were divided, taking into account the anthropometrical characteristics that could affect the usage of the hand-held touchscreen device. As mentioned before, this clustering result will be the base of further analysis. The result is described in the following section.

3.2 Hand Clustering for Touchscreen Device Use

3.2.1 Data selection/extraction result

There were two determinants for hand size and shape. For determining hand size clusters, hand length was used as an input of clustering. Among 61 hand dimensions, 34 were selected. In this case, the number of dimensions was too large increasing computational complexity, so dimension extraction was done by using PCA.

PCA was performed using R studio Version 1.0.136 with R packages. The number of components was selected through scree plot. An elbow point, which is a critical point having a noticeable change in increasing/decreasing rate, was the determinant. The plot indicated that three components were reasonable to represent the information without losing the total variance of the dataset.

Three principal components are associated with eigenvalues which were larger than 1. A scree plot of eigenvalues of the un-rotated factors indicates an 'elbow' of the plot as marked with a circle. This point of the curve is used as the threshold selected for maintaining the initial information extracted from the observed variables and for maximizing the variance accounted for. As illustrated in Figure 10, eigenvalues of the three components were 4.20, 2.06, and 1.55. The three components cumulatively accounted for 71.5% and each retained 52.0%, 12.5%, and 7.09% of the total variance. The shallow line or "scree" to the right away from the circled point represents the rest amount of variance accounted for the subsequent minor components which would not be used for further part of the study.

The first component represented hand length and perpendicular palm length negatively. The hands which possessed lower component score were bigger hand. The second component strongly associated with finger dimensions such as breadth of five fingers (distal) and first and second phalanx length of fingers excluding the thumb. The breadths were signed negatively, and lengths were signed positively; this means higher component score was related to a thin and long finger. The last component consisted of dimensions related to vertical and horizontal dimensions of palm and radial styloid-thumb fingertip length. The vertical dimensions had a negative sign and the horizontal dimensions did a positive sign. Therefore, hands with higher component scores have a larger horizontal ratio. For the latter part of the study, the first, second and third components were named as hand length (negative), finger ratio and palm ratio, respectively. The result of PCA is presented in Table 4. PCA result with three components.

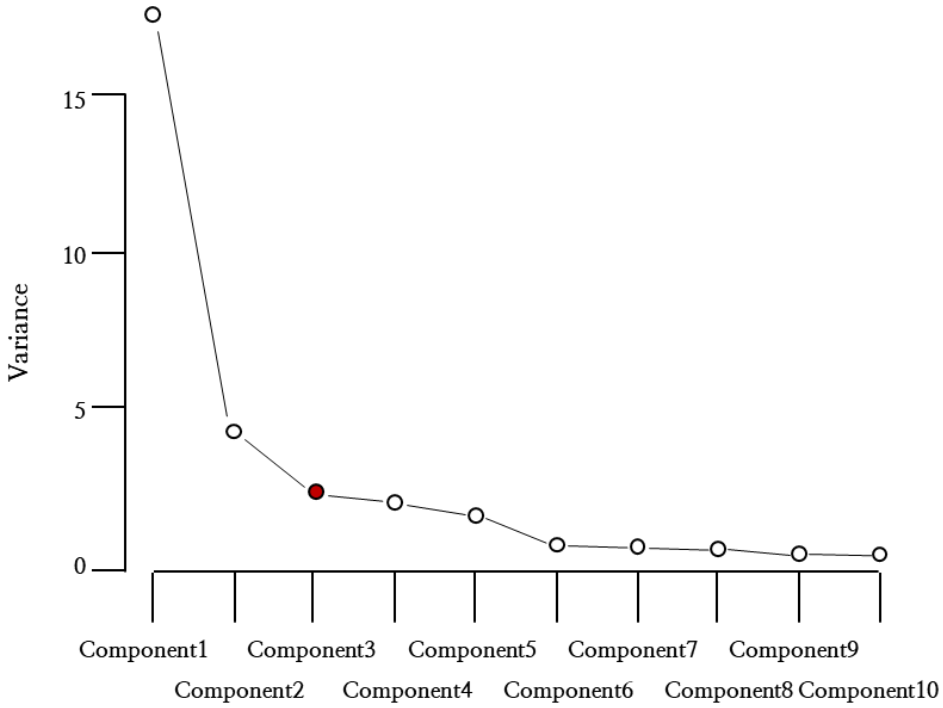


Figure 10. A scree plot for hand dimensions

Table 4. PCA result with three components

Hand dimensions	Component		
	1 Hand length	2 Finger ratio	3 Palm ratio
Finger breadth distal - Thumb	-0.170	-0.248	0.044
Finger breadth distal – Index	-0.173	-0.231	0.087
Finger breadth distal – Middle	-0.174	-0.235	0.064
Finger breadth distal – Ring	-0.171	-0.234	0.080
Finger breadth distal - Little	-0.163	-0.251	0.068
Hand breadth	-0.196	-0.130	0.011
Hand thickness	-0.157	-0.184	0.066
Hand Length	-0.220	0.058	-0.116
Radial styloid-thumb fingertip length	-0.180	0.019	-0.274
Palm length perpendicular	-0.200	-0.049	-0.167
Capitate-Finger first crease line length - Thumb	-0.167	-0.077	-0.358
Capitate-Finger first crease line length - Index	-0.199	-0.059	-0.252
Capitate-Finger first crease line length – Middle	-0.196	-0.063	-0.280
Capitate-Finger first crease line length – Ring	-0.190	-0.055	-0.275
Capitate-Finger first crease line length - Little	-0.184	-0.056	-0.289
Thumb-finger first crease line length - Index	-0.147	-0.118	0.326
Thumb-finger first crease line length – Middle	-0.167	-0.119	0.297
Thumb-finger first crease line length – Ring	-0.174	-0.129	0.272
Thumb-finger first crease line length – Little	-0.182	-0.122	0.222
Thumb length	-0.196	0.057	0.134
Index finger length	-0.198	0.193	0.041
Middle finger length	-0.204	0.182	0.020
Ring finger length	-0.205	0.170	0.012
Little finger length	-0.186	0.183	0.040
First phalanx length – Thumb	-0.145	0.148	0.192
First phalanx length – Index	-0.109	0.282	-0.010
First phalanx length – Middle	-0.129	0.236	0.001
First phalanx length – Ring	-0.123	0.213	-0.038
First phalanx length - Little	-0.116	0.226	0.032
Second phalanx length – Thumb	-0.179	-0.085	-0.048
Second phalanx length – Index	-0.143	0.208	0.118
Second phalanx length – Middle	-0.134	0.208	0.081
Second phalanx length – Ring	-0.148	0.217	0.133
Second phalanx length - Little	-0.124	0.212	0.073

3.2.2 Comparison of the result from three clustering methods and validation

From three components from PCA, three types of cluster analysis were performed to divide hands into three types. The component scores were used as the input variable for the analysis. The required number of clusters was greater than two for further information and based on the relative criteria, BIC, three clusters seemed to be best according to the LPA result as shown in Figure 11 and Figure 12.

The clustering results k-means and c-means are as shown in Figure 13. Among the three components, only the first components worked as the determinant of clustering; the three groups were divided into the small, medium and large size of a hand. To verify this statistically, ANOVA tests were performed. The results showed that only hand length (component 1) distinguished the groups whereas the groups were not differed by two other components.

On the other hand, the result achieved from LPA, as described in Figure 14, were more complicated than those two results. The hand length (component 1) and palm ratio (component 3) worked as the determinants to distinguish the three groups according to ANOVA results.

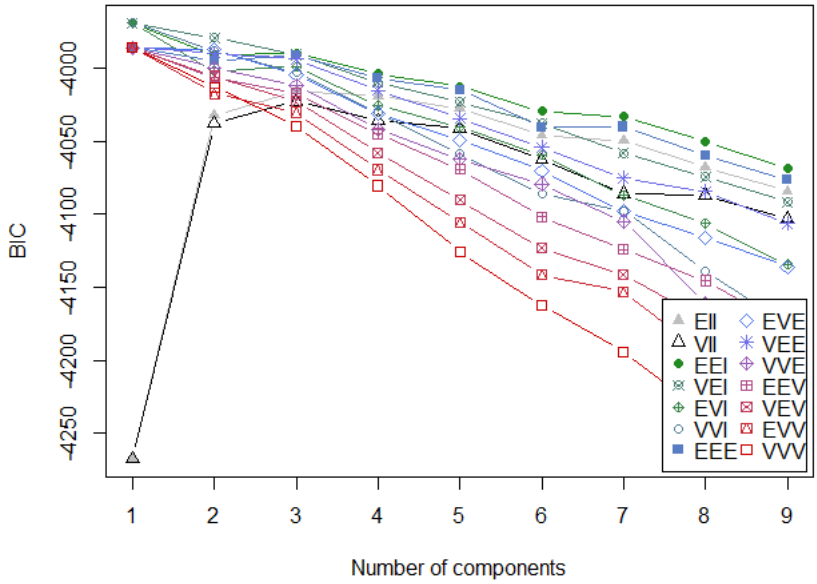


Figure 11. BIC comparison for models and the number of components

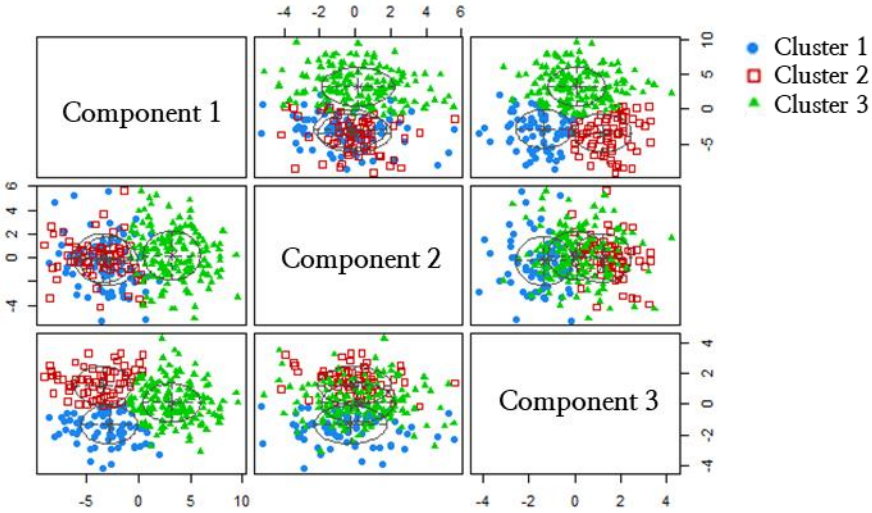


Figure 12. Distributions of hand clusters for each component

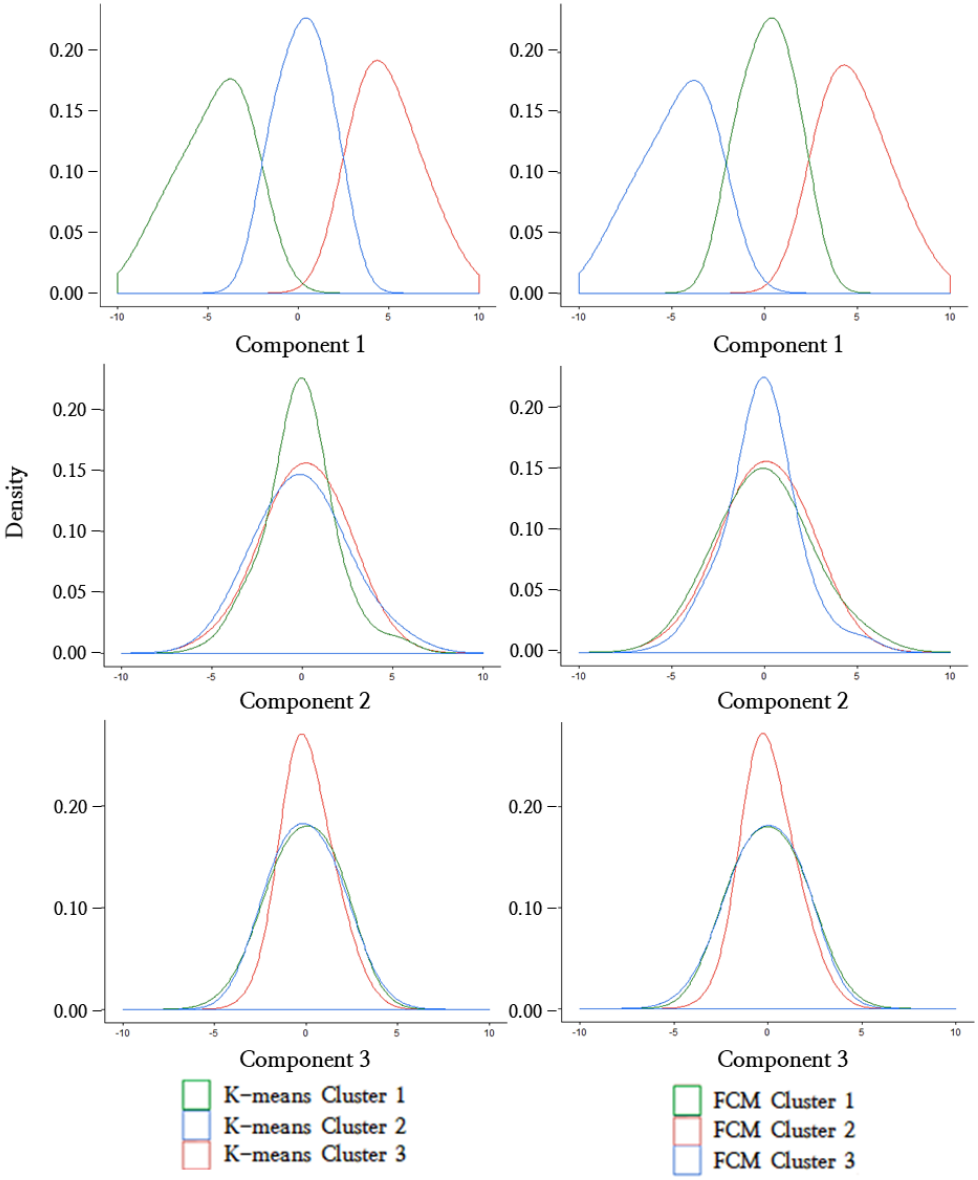


Figure 13. Distributions of the components for three clusters: K-means (left) and FCM(right)

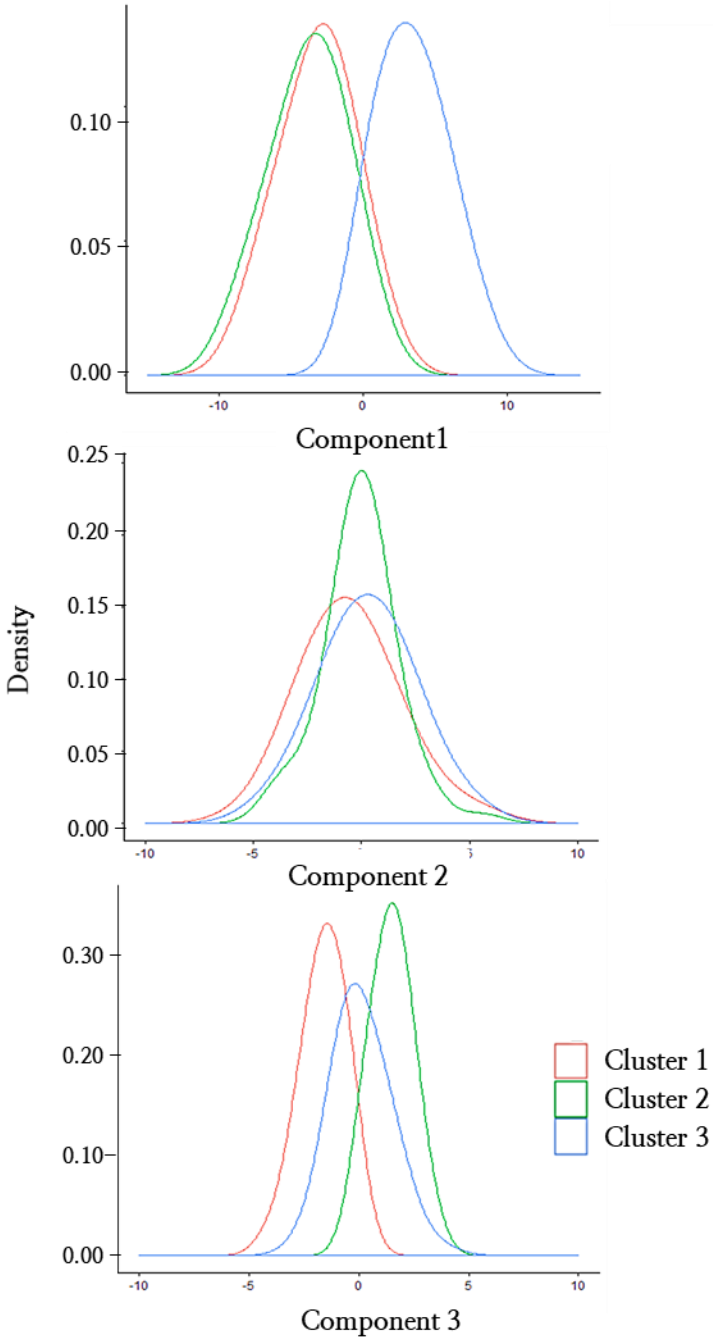


Figure 14. Distributions of the components for three clusters (LPA)

The result of three clustering analysis showed accordance of 0.967, 0.332 and 0.327 in the order of pairs, k-means and c-means, LPA and c-means, k-means and LPA. The accordance was identified in terms of ARI which defined as the number of pairs of objects in the same subsets or in different subsets of two clustering results divided by the total number of pairs of objects including the number of disagreements between the results Crosstables indicating corresponding groups for other clustering methods are following (Table 5, Table 6 and Table 7).

3.2.3 Interpretation

As mentioned previously, the clusters achieved through the k-means and c-means clustering showed almost identical results in which the three hand types were named as a small, medium and large hand. The hand length played a role as a criterion. However, LPA could explain the clusters by using not only hand length but also palm ratio. This result explained human hand more complicatedly by taking palm ratio account into clustering, not just dividing the clusters by hand length.

According to the result from LPA, group 1 and 2 have larger hand than group 3. The difference between group 1 and 2 is the length of the palm; group 1 has the smallest palm length and group 3 does the largest palm. In other words, assuming that the group 1 and 2 have the same length of the hand, group 1 has longer finger and shorter palm than group 2.

Table 5. Cross table – k-means and FCM

		c-means		
		1	2	3
k-means	1	0	2	101
	2	96	0	1
	3	0	87	0

Table 6. Cross table – LPA and FCM

		c-means		
		1	2	3
LPA	1	47	0	26
	2	49	0	19
	3	0	89	57

Table 7. Cross table – k-means and LPA

		LPA		
		1	2	3
k-means	1	23	18	59
	2	47	50	0
	3	0	0	87

To statistically approve the difference between groups, one-way ANOVA was conducted to compare the effect of hand type on components of hand length, and two Kruskal-Wallis tests were performed to inquire the effect of finger ratio and palm ratio at the $p < 0.05$ level. Each test was done after Levene's Test for Homogeneity of Variance; except hand length component, no component was satisfied homogeneity of variance. The results are shown below

- Hand length (component 1): ANOVA, F (2, 284) = 353.5, p-value < 0.001
- Finger ratio(component 2): Kruskal-Wallis test, chi-squared = 8.378, df = 2, p-value = 0.01516
- Palm ratio(component 3): Kruskal-Wallis test, chi-squared = 146.84, df = 2, p-value < 0.001)

Through several post-hoc tests, the differences between the groups were found, too. The result from Tukey's post-hoc test showed that group 1 and 2 were identical for component 1 (hand length), but group 3 was significantly small compared to the others. By performing pairwise Wilcox tests, it was found that group 1 was distinguished from group 3 in terms of component 2 (finger ratio) and regarding component 3, all groups were significantly different from each other.

3.3 Conclusions and Discussion

This chapter aimed to figure out the most appropriate way to cluster human hand type with hand dimensions related to the touchscreen device usage. To this end, hand type was classified after selecting hand dimensions which were considered to be related to using of the devices. As a result of the comparison to identify a better method for hand classification, it was found that LCA provided the most appropriate clustering result.

The components representing hand dimensions were found by PCA. Three components were identified, hand length, finger breath and length and palm ratio. This result meant that those three components were likely to be independent of each other. That is, longer hand length is not necessarily correlated longer fingers or palm. Opposite to this, fingers were highly related to each other.

With these components, the hands of the Korean population was categorized into three hand types. Three clustering methods, k-means, fuzzy c-means and LPA methods were selected and performed. By comparing the results, it was found that the first two methods were similar in the aspect of clustering criteria which was hand length as well as clustering results. On the other hand, LPA utilized two criteria, hand length and palm ratio, to categorize the hand type. The clustering accordance of LPA and other methods were much lower than the accordance of k-means and FCM.

Most previous studies on human hand clustering treated hand length as a determinant by using the k-means clustering method. This classification method is simple and useful when the range or spectrum of grasp is narrow or limited, but for

diverse grasp such as repositioning, the motion becomes more complicated. In this case, the result from LPA which considered more hand shape components is regarded more useful.

For the latter part of this research, the result achieved from LPA analysis was selected to define hand type in order to explain human hand through not only size but also another component, which was the ratio of palm and fingers in this case. According to LPA, the hand type was categorized as a large hand with long fingers, the large hand with relatively short fingers and a small hand.

LPA could include another component beyond hand length so that the hand shape could be reflected for clustering. This method can be applied to other clustering studies which classify hand or body shapes having with its advantage reflecting distributions other than normal distribution. According to the dataset and the purpose of the dissertation, common k-means or fuzzy c-means clustering may not be the best for cluster analysis.

This study, nonetheless, has a limitation regarding the robustness of hand dimension measure. The landmarks to measure hand dimension were relatively unstable. For example, some participants had very thick crease line and this made measuring joint length difficult. Also, fingers were irregularly shaped, so it might be better to classify hand shape based on 3D scanning or image-based methods such as convolutional neural network or support vector machine algorithm.

The hand clusters defined as a conclusion of this chapter will be applied to further analysis in later part of this research.

Chapter 4. Muscular and Postural Synergies

In this chapter, muscular synergies and postural synergies will be defined by collecting and analyzing sEMG and joint angle data. In the beginning, an experimental design will be introduced including participants and measurement, as well as measuring apparatus. Six muscles and ten joint angles of fingers were selected based on the result of the literature review described in Chapter 2. In the experiment, the participants were asked to grasp various objects including the handheld touchscreen device and operate the device to collect the data required to define the synergies. Since both muscular and postural synergies can be achieved from dimension reduction techniques without losing information that the original data contains, the PCA method was able to be applied to the data collected. In order to measure the joint angles, a measuring device which is not like the glove was developed.

Based on the result achieved from this chapter, the grasp classification and hand motion analysis will be done in Chapter 5 and 6.

4.1 Experimental design

4.1.1 Participants

In this study, 14 participants (eight males and six females) were recruited for an experiment. Their ages were ranged from 25 to 36, 30.1 on average. As defined in Chapter 3, they were assigned to correspond hand types after measuring the hand dimensions. Three, four and seven participants belonged to group 1, 2 and 3, respectively. The participant did not have any kind of hand-related disease or musculoskeletal problems such as carpal tunnel syndrome, which can affect hand functions. The ages of the participants were ranged from 20 to 35. All participants who were right-handed had their own smartphones and were familiar with the device.

4.1.2 Measure

During grasping, two types of data were recorded, EMG and joint angle. EMG measure, six muscles were selected: Three extrinsic muscles, extensor digitorum (ED), flexor digitorum superficialis (FDS) and abductor pollicis brevis (APB) and three intrinsic muscles, flexor pollicis brevis (FPB), abductor pollicis brevis (APB), first dorsal interosseous (FDI). Many studies related to inquire use behavior of smartphone often employed EMG measure on the intrinsic and extrinsic muscles listed above [18, 25, 33, 34, 129-132]. The studies targeted muscles which were associated with thumb movement including abduction, adduction and opposition, flexion and extension of fingers. Having slightly different choices, this research measured EMG data of the six muscles.

Regarding joint angle, ten joints were selected to be measured among 22 joints which construct human hands. The joints consist of five metacarpophalangeal joints (MCP 1–5), one distal interphalangeal joint of the thumb (IP) and four proximal interphalangeal joints (PIP 2–5). It is ideal to measure all the joints, but due to technical limitation, only angles of ten joints were measured. Also, there was sufficient evidence to exclude measuring DIP joints. Some studies suggested that the angles of DIP joints could be expected by the ones of PIP [133]. The studies provided a mathematic model for calculating an angle of DIP as a function of the corresponding PIP angle. Also, it is known that covariation in the motion at those MCPs, IP and PIPs are in charge of grasping [134]. In contrast to EMG, few numbers of previous studies related to smartphone usage analyzed joint angles, as the author's knowledge.

4.1.3 Tasks

This chapter attempts to define the universal synergy of muscle and posture. Tasks performed in this dissertation were divided into two categories: grasping objects and operating a touchscreen device. More details about the grasp and operation tasks will be described in Chapter 5 and Chapter 6, for each.

4.1.4 Data analysis

EMG signals

Comparisons of sEMG values within or between individuals involve potential problems. Differences between different recording sites and between individuals lead to the prudent use of such comparisons. The factors affecting these differences can be

the thickness of the subcutaneous tissue, muscle resting length, the velocity of contraction muscle mass/cross-sectional area, age, sex, subtle postural changes, inter-electrode distance and skin [135]. This means the comparison of amplitude measurements only for muscle activity may be misleading without first standardizing sEMG data. The collected raw EMG data, therefore, must be normalized.

There are two ways to normalize EMG data: Maximum voluntary contraction (MVC) and reference voluntary contraction (RVC). Both methods determine what a reference value is and what percentage of the value it corresponds to. The MVC is based on the RMS value when the subject has a maximum isometric contraction on the muscle, while the RVC is based on the RMS value when taking a specific action. MVC appears to be more sensitive to contractions that require higher levels of efforts and loses its sensitivity at low levels of effort. The RVC is most appropriate when lower levels of activation are to be assessed or analyzed. Also, this may depend on the type of muscle. Thus, it is not possible to select one perfect normalization technique for all occasions. According to previous studies, the average %MVC for tapping, dragging or typing task with handled touchscreen devices was ranged from 5% to 20% [106]. Therefore, in this study, RVC looks more reasonable as a normalizing method since tasks require a low level of muscle activation.

RVC measure for each muscle was similar to measure MVC in the experiments. Except for APB and FDS which were related to flexion, the participants were asked to extend or abduct hand with a bare hand. In other words, the participant had no object to push and this led to generating the sub-maximal contraction of the muscle. They were asked to keep the same postures when measuring RVC.

Joint angle and gyro data

A customized system was developed to record the joint angles of the human hand from the 10 sensors from the beginning time to the completion time during each task. The sampling rate was 7–8 Hz. Prior to measuring the angles, the sensors were calibrated by mapping values of degree and resistance using the angular meter. The details of the customized measuring system are introduced in the next section.

Principal Component Analysis

PCA, among dimension reduction techniques, was employed to investigate the coordinated patterns among the selected muscles and joints of the hand. Then, an analysis of correlation was performed to determine the coordinated relationships between muscles, joints and a combination of them. Many studies choose PCA to denote postural or muscular synergies [51, 52].

4.2 Apparatus

EMG measurement

In this experiment, Laxtha EMG System (Laxtha Inc., Korea) was utilized. The EMG signals were monitored in real time to control the quality and simultaneously recorded on-line at 1024Hz by using Laxtha's WEMG 5308 system and software, Telescan™. The EMG signal recorder was wireless, so unnecessary noise could be avoided. The raw EMG signal was band-pass filtered between 13 - 430 Hz. Two EMG parameters were extracted from the raw EMG signal. The RMS value of rectified EMG was calculated to quantify the muscle activity. The reference electrode was attached either on elbow bone or radial styloid process. As right-sided proximal postural and distal muscles were involved in the task, only the EMG data from the right-sided postural proximal muscles and distal forearm/hand muscles were collected and reported in this study. Bipolar surface electrodes of 33mm diameter were used (3M). If required, the electrodes were cut as much as a conductor is not damaged. The specific locations of EMG electrodes were referenced to past research studies. In the beginning, subjects' skin was gently cleaned with alcohol prior to attaching electrodes.

Joint angle measurement

In order to measure joint angles, a customized glove was designed. The glove consisted of ten simple flex sensors, 'Flexible Bend Sensor', 56 mm in length, and one 9-DOF gyro sensor, 'Adafruit Flora'. As the flex sensors were bent, the resistance changes and angles could be obtained to the extent of its changes. The existing grove-

type measuring devices could not allow natural hand behaviors due to the slippery surface, thickness and unfitted size of the gloves. In fact, through a pilot test, it was concluded that the conventional device, 5DT data glove, could not be utilized for this experiment. Since the sensors were attached covering the joints on the dorsal side without crossing the palmar side, this new measuring system had the advantage that the existing data gloves did not possess. In addition to flex sensors, a gyro sensor which was attached on the back of the hand were used to record tilting angles of the hand. In the case of the gyro sensor, x-axis was aligned along the bone of the participants' middle finger. This made it possible to change the location of the sensors to the most appropriate position and allowed the participants to control the device with minimal disturbance compared to the one caused by the glove-type devices. The sensors are shown in Figure 15.

The data capturing system utilized was constructed from an Arduino development board, Arduino Mega2560 which was a microcontroller board. Arduino Mega2560 contains 54 digital pins of input /output of which 16 pins could work as analog inputs, 15 pins as PWM outputs and 4 pins as universal asynchronous receiver/transmitter (UART, Serial Port Hardware), 16 MHz crystal oscillator, a USB connection, power, header ICSP and a reset button. (These were known as what supported the microcontroller.) Through connecting this board to a computer via USB cable, it is connected to AC-DC adapter to start to activate it. Arduino provides general codes and libraries for each sensor. Sensors of the glove and electrodes of sEMG attachment are illustrated in Figure 16 and Figure 17.

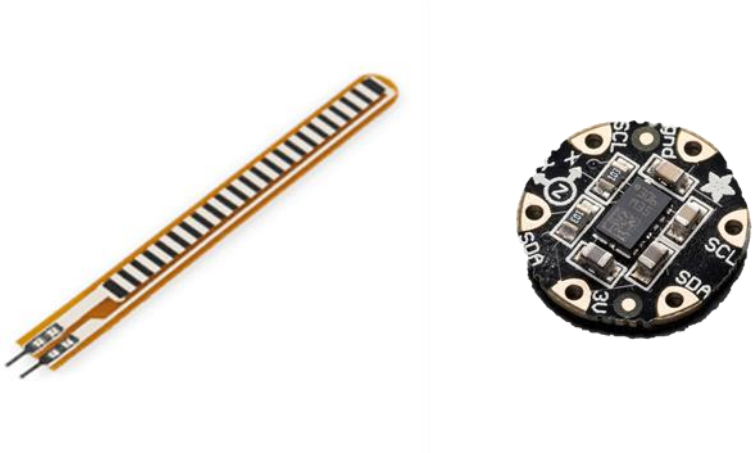


Figure 15. A flex sensor (left) and a gyro sensor (right)

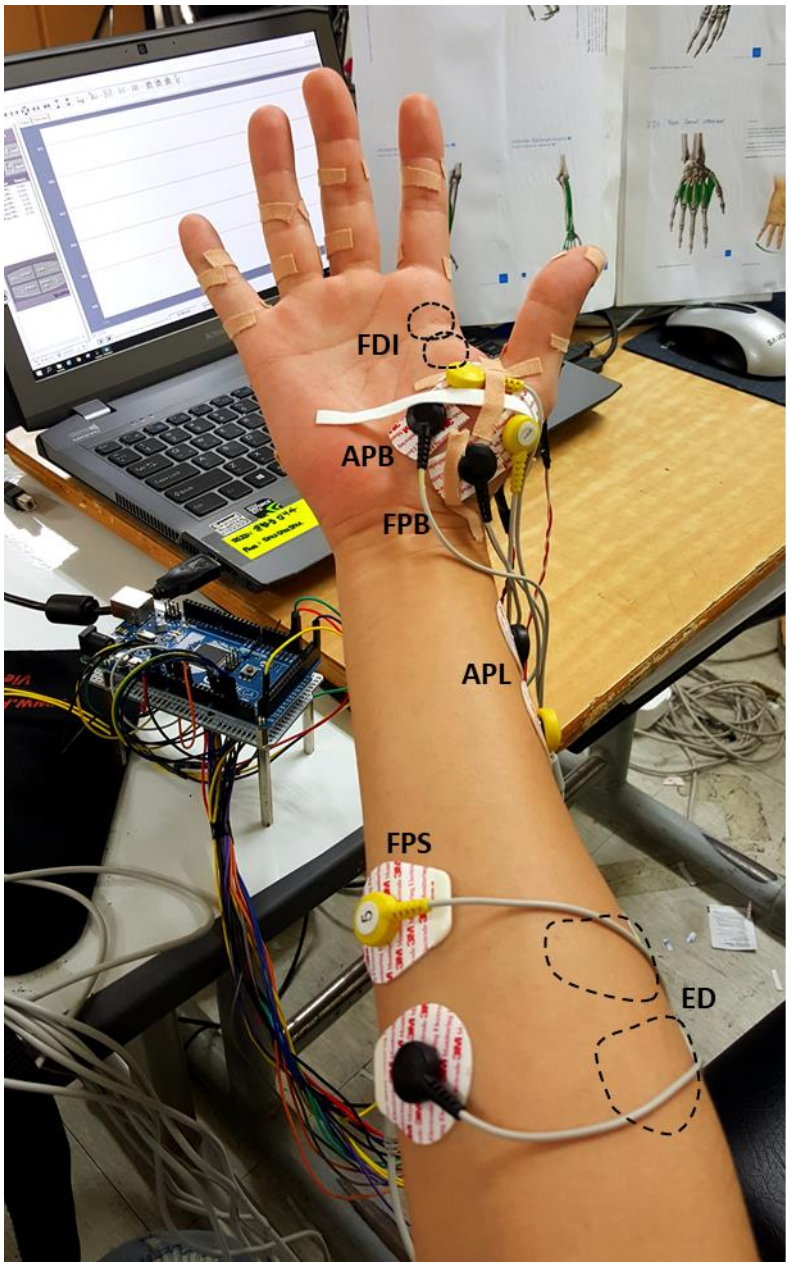


Figure 16. The six electrodes of sEMG attachment

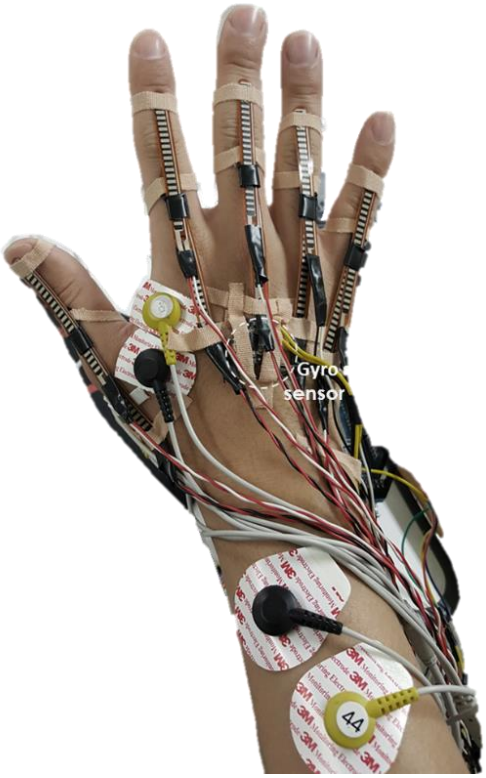


Figure 17. Ten flex sensors and a gyro sensor of the customized data glove attachment

4.3 Muscular Synergy

PCA was performed to find or factorize both muscles and joint angles to define synergies. The analysis was done by operating R studio Version 1.0.136 with R packages, called 'stat'. The number of components was determined by their eigenvalues which were greater than one. As Figure 18 shows, two components were selected explaining variance which the original data had enough. The components became muscular synergies and each synergy was characterized by a dominant group of muscles with relatively high weights. The four remainders with low or even zero weights were not considered to analyze hand motions.

From the sEMG data, two muscular synergies were generated. One muscle was influential for more than one synergy, but it was predominated in one synergy and showed lower weight in other synergies. The conclusion that a single muscle may be a member of more than one muscle synergy is in agreement with the results of a series of studies by Bizzi and his colleagues [136]. As Figure 18 indicates, two components associated with eigenvalues which were larger than one seemed to be reasonable to represent the information. As the number of components increased, the variance that the component accounted decreased.

Eigenvalues of the two components were 2.57 and 1.28. The components cumulatively accounted for 64.3% as illustrated in Figure 19 and each retained 23.0% and 21.3% of the total variance. The components located right side to the circled point represents the rest amount of variance accounted for the minor components and would not be used for further part of the study. The number of variables explaining muscle

activities was then reduced to two from six.

As indicated in Table 8, the first component was represented by APB, FPB and ED, and lower component scores corresponded to more activation of these muscles which were related to thumb flexion and finger extension. Other muscles were positively related to the dominant muscles. The second component was associated with FPB, FDI, and APL. FDI and APL were correlated positively, but FPB was in the opposite way to them, thus high scores of this component were related to the abduction of thumb and low scores were related to the extension of thumb and abduction of index finger towards the thumb.

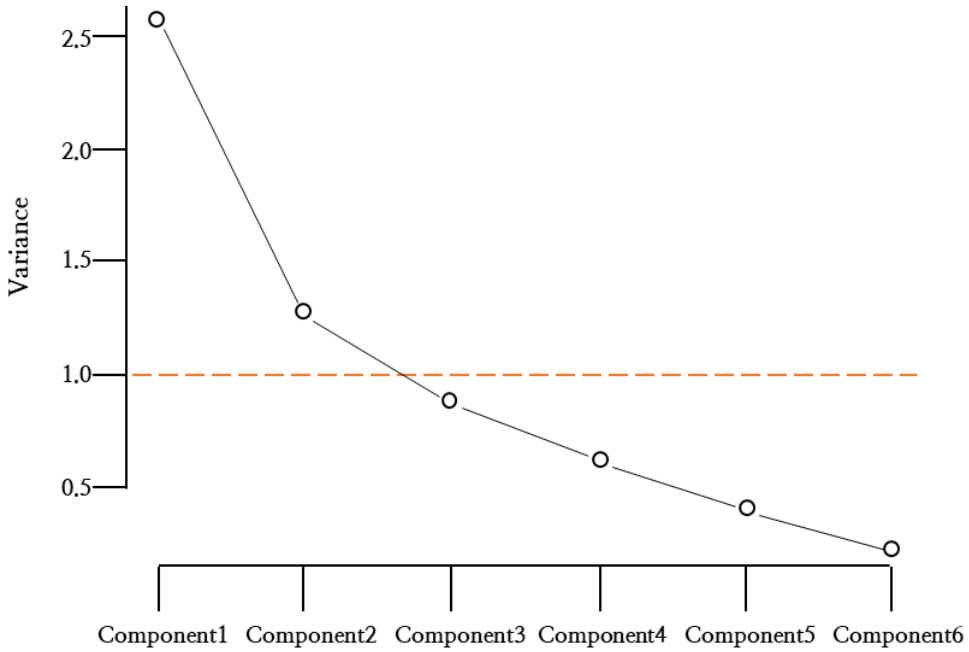


Figure 18. A scree plot of PCA on sEMG features as the number of components (muscular synergies) increases

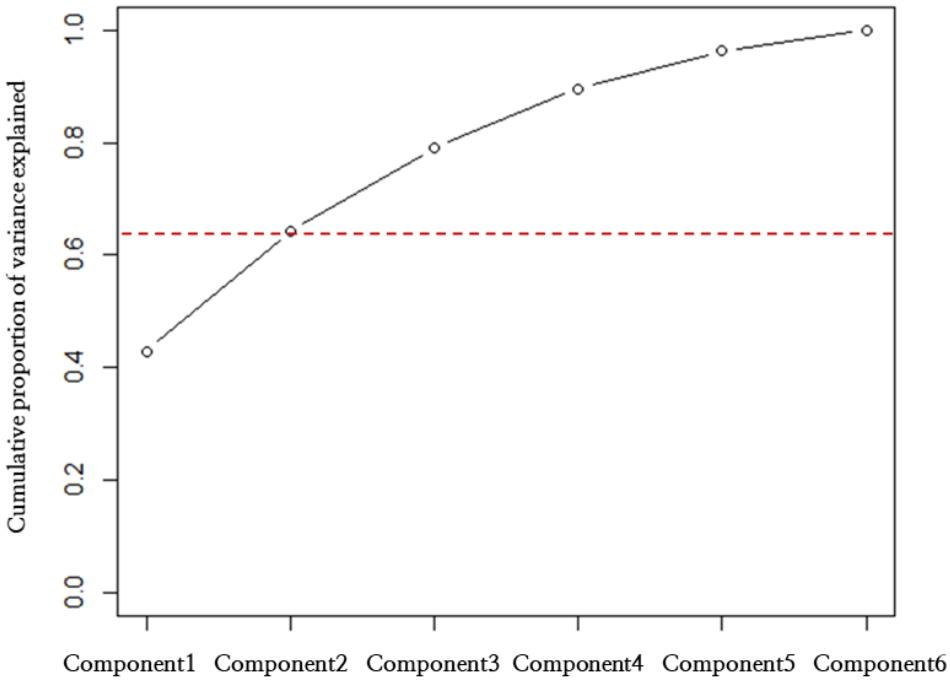


Figure 19. Cumulative proportion of variance explained as the number of components (muscular synergies) increases

Table 8. PCA loadings of sEMG data with the absolute cut value 0.43

Muscles	Component	
	1	2
APB	−0.492	0.418
FPB	−0.461	0.465
FDI	−0.255	−0.607
APL	−0.385	−0.438
FDS	−0.331	−0.215
ED	−0.472	

4.4 Postural Synergy

In the case of joint angle, three components were defined as the postural synergies according to the result of PCA. The plot indicated that three components accounted for 76.3% of total variance with eigenvalues greater than one as shown in Figure 21. The scree plot is on Figure 20. Eigenvalues of the three components were 4.93, 1.41 and 1.29 in the order of component 1, 2 and 3 which had 49.3%, 14.1% and 12.9% of the total variance, respectively. Only three components were used for the analysis of the latter part of this study, instead of ten finger joint angles.

Table 9 shows the result of PCA from joint angle dataset. The first component represented MCP 2 to 5 and PIP 2 to 5 which were related positively, which means higher component score corresponded to higher degrees of extension of the first and second joints of fingers (2–5). The second component was dominantly associated with MP and IP which were positively related, weakly with MCPs. PIP 2 to 4 were weakly related to the component in opposite directions. This indicates that higher component score was mapped to a higher degree of thumb, less high degree of the first joints and flexion of second joints of the index, middle and ring fingers. The last component was associated with first and second joints of middle and ring fingers with opposite signs between joints. MP was positively related to the second joints. Therefore, with flexing thumb and the second joints of the fingers, the first joints of them were extended if the score of the component gets high and vice versa. Figure 22 shows the result of visualization of the posture according to the postural synergies changes.

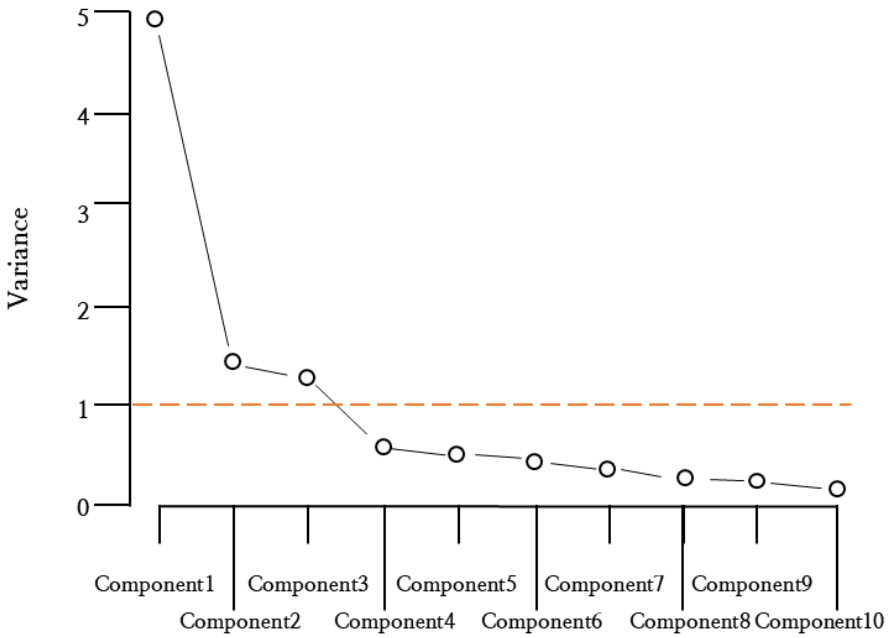


Figure 20. A scree plot of PCA on joint angles

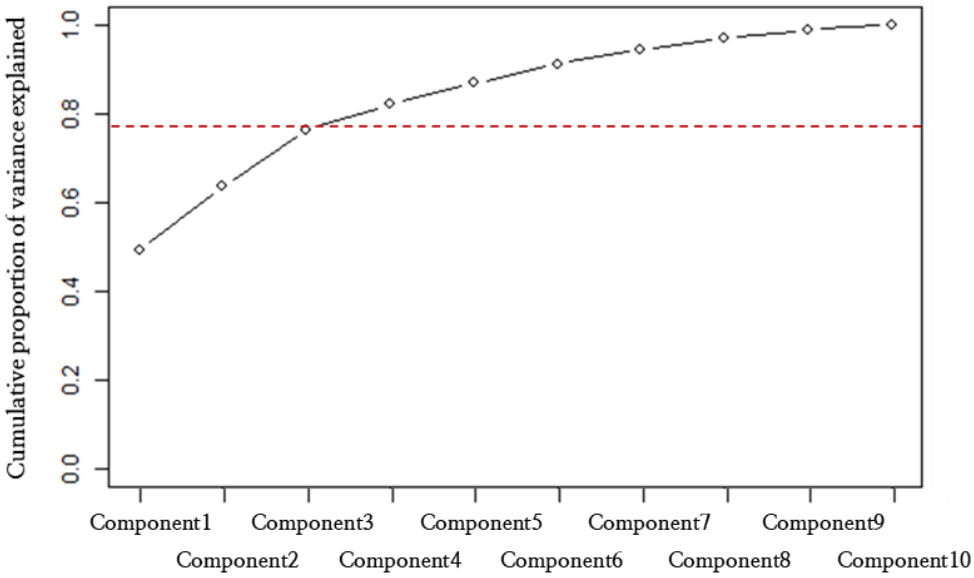


Figure 21. Cumulative proportion of variance explained as the number of components (postural synergies) increases

Table 9. The PCA loadings of joint angle data with the absolute cut value 0.32

	Component		
	1	2	3
MP		0.6	0.464
MCP2	−0.339	0.274	
MCP3	−0.346	0.254	−0.333
MCP4	−0.354	0.203	−0.309
MCP5	−0.34	0.165	−0.277
IP	0.176	0.571	0.224
PIP2	−0.371	−0.157	
PIP3	−0.327	−0.23	0.461
PIP4	−0.335	−0.168	0.459
PIP5	−0.369		0.141

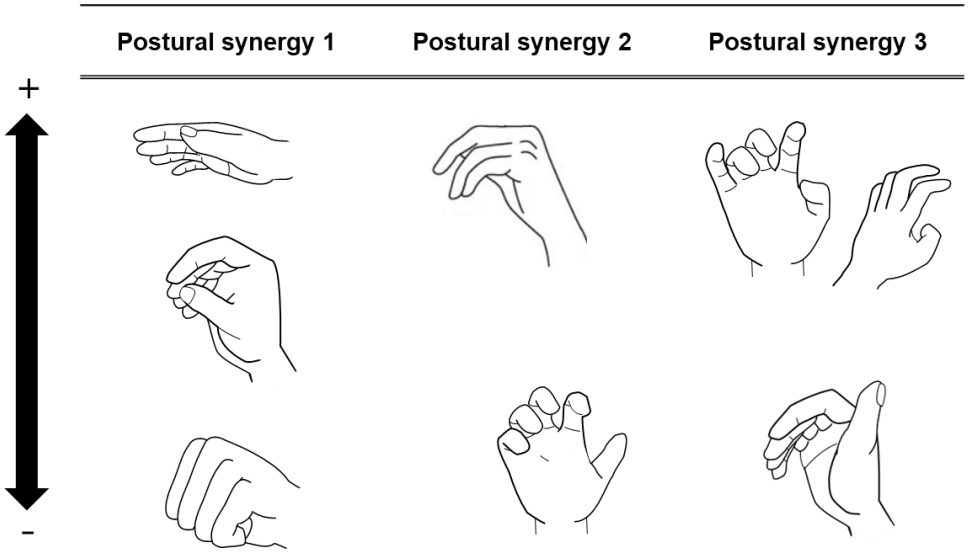


Figure 22. Illustration of postural synergies

4.5 Conclusion and Discussion

In this chapter, muscular synergies and postural synergies were defined by collecting and analyzing sEMG and joint angle data. Six muscles which were APB, FPB, ED, FDI, APL, and FDS and ten joint angles of fingers, MP, MCP2-5, IP and PIP2-5, were selected for this analysis.

According to the result PCA, it was found that muscular and postural synergies existed. Three components could explain 70.6% of the total variance of ten joint angles, and two components could account for 61.0% of the total variance of six muscle activities. The amount of the corresponding variance could be the evidence of synergy existence.

The activation of a given muscle of human hand is related to the positions of numerous joints, not just those that are directly linked to the muscle when grasping objects. One source of synergies is the biomechanical structure of the hand, in which tendons activated multiple digits at the same time, while the related muscles share common bases, is one source for the synergies [51]. This can explain one muscular synergy can operate or control multiple digits. Also, FDS and FDP which correspond PIP and DIPs are activated together due to its entangled structure of tendons. However, ED which is in charge of MCP extension activates as an antagonist, postural synergy 2 and 3 can be explained.

Regarding muscular synergies, spinal circuitry, mapped only to a small extent to the human hand, co-activates muscles which define synergies. With the goal of

exploiting the minimum number of muscles necessary for decoding the reference profiles, in the other studies used the major finger antagonist muscle pair – the ED and FDS [6, 48].

Two muscular synergies and three postural synergies activate independently as the way of the PCA works, and in the next chapters, the analysis will be performed based on the synergies defined in this chapter.

Chapter 5. Grasp behavior Analysis

For good design of hand tools, human grasp behaviors should be fully understood by defining grasp types. This can begin with grasp classification. Classifying grasp is useful in assessing the force and precision involved in the tasks because the types of grasp affect the contact area and force application points. Different assumptions about required force and its application points are made for each type of grasps. Once the type of grasp is defined, it is possible to design hand tool appropriately.

In the previous researches, grasp has been classified according to characteristics of the task or object. For example, the grasps were divided into a power and precision grasps. In addition to this classification, the grasps can be categorized as cylindrical, tip, hook, palm, spherical and contour grasps. These approaches were all top-down methods and no such classification based on hand motion data was developed robustly.

Moreover, due to the diversity of hand tools, the existing classification even does not cover all types of object. The grasp for a smartphone which is one of the most used devices in the recent era is missing in the existing grasp taxonomies. So far, studies related to grasping the hand-held devices are very limited both quantitatively and qualitatively. Lee [23] explored and defined smartphone grasp behaviors, but not connected to the existing classification systems such as Cutcoskys [83] or others [89].

The purpose of this chapter is to supplement current grasp taxonomy by adding smartphone grasp. In order to achieve this goal, the followings will be accomplished

in this chapter: using defined muscular and postural synergies through dimension reduction technique in the previous chapter, 1) identifying grasp in terms of the synergies for existing grasp types, 2) allocating the grasp for smartphone to the existing classification system and 3) figuring out the difference among the hand groups defined from Chapter 3.

5.1 Experimental design

5.1.1 Experimental design

In this study, the handheld touchscreen device grasps were identified and classified into the existing taxonomy in terms of muscular and postural synergies. Human manipulation taxonomy refers to the study conducted by Fiex [89, 137], and among the 33 grasp types, 14 grasps which were considered as smartphone-related grasps were selected through the pilot test as listed in Figure 23.

The objects selected for the grasps were a tennis ball, ping-pong ball, two cylinder type bottles having different diameters, the lid of the bottle, a disk type glass, dumbbell, supplementary battery, a plate, a booklet and lastly, a smartphone. Figure 24 depicts the objects and the ways to grasp them.

Dependent variables were sEMG and joint angle data as well as their synergies and independent variables were types of grasp. The operations were done by a single, preferred hand in the fixed experimental environments, such as place, room temperature, and humidity. If a muscle gets fatigue, the amplitude of the EMG signal tends to be greater during submaximal isometric contractions. For this reason, it was avoided to have fatigued muscles through taking rest in the experiment to collect more accurate data.

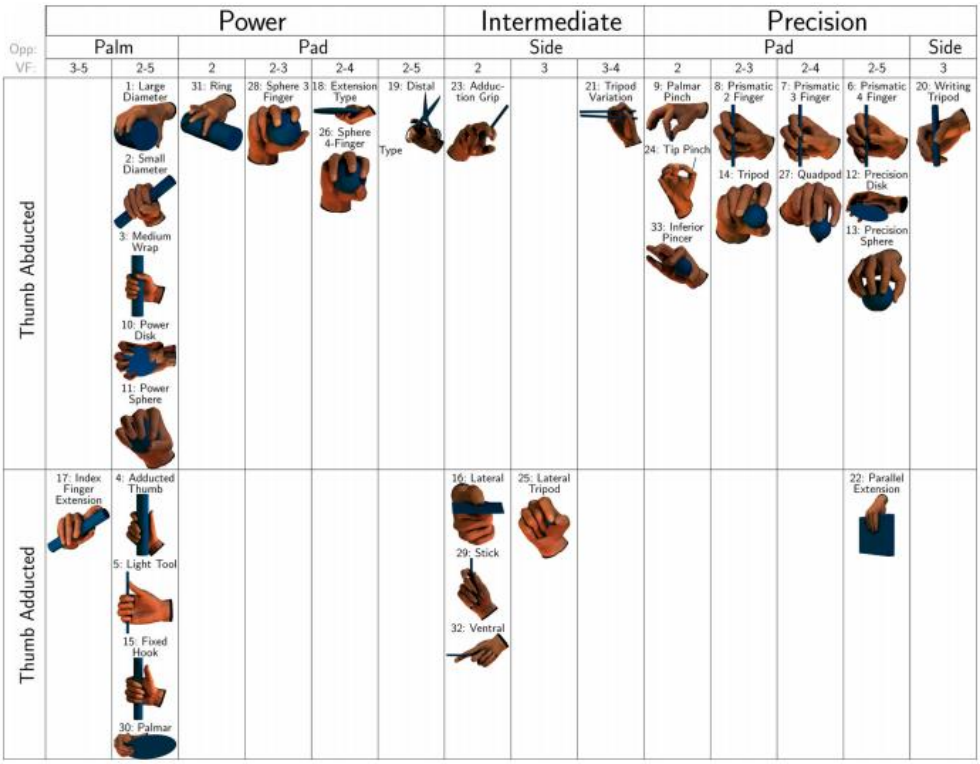


Figure 23. The classification of grasps by Feix et al. [89]

Figure 24. The objects and the corresponding grasps*

*The grasp types are numbered in order from top left (grasp 1) to bottom right (grasp 15).

Among the grasps selected from Feix's work, the grasps for scissors, chopsticks and any grasps holding pen-type of objects did not seem to be related to grasping smartphone, so the grasps were excluded in the experiment. Among the selected grasps, nine, one and four types belonged to power grasp, intermediate grasp and precision grasp, respectively. The specific information of objects used to this experiment was listed in Table 10. Grasp number 5, 8, 10, 11, 12 and 14 were thumb-adducted grasps and the rests were thumb-abducted grasps.

The tasks were performed by using a commercial smartphone, Galaxy 8, Samsung. (Figure 25) The size of the device was 148.9 x 68.1 x 8 mm and its weight was 155g.

Table 10. List of objects grasped

Types	Thumb location	Weights	Size	Shape (Object)	Grasp #	Grasp name
Power	Abducted	40	60	Sphere(tennis ball)	1	Sphere 4-fingers
Precision	Abducted	5	25	Sphere (pingpong ball)	2	Tripod
Precision	Abducted	5	25	Sphere (pingpong ball)	3	Quadpod
Power	Abducted	150	50	Cylinder(bottle)	4	Large diameter
Power	Abducted	150	50	Cylinder(bottle)	5	Ring
Precision	Abducted	20	50	Disk(bottle lid)	6	Precision disk
Power	Abducted	140	40	Cylinder(thin bottle)	7	Medium wrap
Power	Adducted	140	40	Cylinder(thin bottle)	8	Adducted thumb
Power	Abducted	150	100	Disk(big lid)	9	Power disk
Power	Adducted	1000	15	Cylinder(dumbbell)	10	Hook
Intermediate	Adducted	52	7	Thin rectangular parallelepiped (battery)	11	Lateral
Power	Adducted	400	250	Big disk(plate)	12	Palmer
Power	Abducted	400	250	Big disk(plate)	13	Extension type
Precision	Adducted	90	7	Thin rectangular parallelepiped (booklet)	14	Parallel extension
N/A	N/A	150		Thin rectangular parallelepiped (smartphone)	15	Smartphone

Figure 25. The touchscreen device used in the experiment (Galaxy S8, Samsung)

5.1.2 Data analysis

The experiment in this chapter was analyzed based on the muscular and postural synergies as described in Chapter 4.

ANOVA tests and post-hoc tests

To compare muscle synergies and postural synergies by the object or hand types, ANOVA tests were conducted. Once ANOVA proved the significant difference between objects or hand types, post-hoc tests could be performed to find where the differences occurred or to confirm the effect of hand type on hand grasp behavior. In this study, Student-Neuman-Keuls(S-N-K) method was selected for the post-hoc test. It is known that if the purpose to obscure the presence of homogeneous groups without the need for a simultaneous verification as a result of the comparison, it is recommended to use the S-N-K method [138]. The statistical analyses were performed by running R Studio version 1.0.136 with the R packages and SPSS (IBM, version 23).

Visualization

In order to understand the grouping grasps better, visualization would be very helpful, especially, when figuring out the distribution or location of each grasp and checking which grasps showed similar and different patterns. Also, in the case that three dimensions were considered together, a 3-dimensional (3D) plot was more intuitive than three 2-dimensional (2D) plots, so the clustering result based on three postural synergies was plotted on the 3D spaces.

5.1.3 Procedure

At the beginning of the experiment, hand dimensions of the participants were measured by a digital Vernier caliper (Mitutoyo) and tape measure. Then, the participants were seated in a chair with arms comfortably near a table on which the measuring apparatus was located. Electrodes including reference electrode were attached to appropriate locations of forearm and hand. Through simple muscle activation, the locations of the six muscles were detected, and the electrodes were attached on the most appropriate points not to disturb the use of the device. After attaching the electrodes, they measured reference voluntary contraction (RVC) for six selected muscles, each. The participants activated each muscle in given manner and a given posture; they were asked to hold their elbow angle 90 degrees during measuring RVC. The raw EMG data were processed into the root mean square (RMS). To normalize the EMG signals recorded for each muscle, the mean RMS of 3 trials of 5-s RVC was calculated for each muscle at the manual muscle-testing positions recommended by Cram et al. [135].

After measuring hand dimensions and RVC values, 15 objects described in Figure 24. The objects illustrated in Figure 24 were provided to the participants and they were asked to grasp as instructed in Figure 23 attaching the electrodes and flex sensors.

5.2 Biomechanical Analysis of Grasp Tasks

5.2.1 Analysis of the grasp taxonomy

Based on the muscular and postural synergies defined in Chapter 4, 15 types of grasp were grouped by testing ANOVA (Table 11 and Table 12) and consequent post-hoc tests integrated to classify the grasps (Table 13). Each postural synergy divided the grasps into six groups. Two muscular synergies divided the grasps into four and three groups for each.

First of all, the power, precision and intermediate grasps were not clearly connected to the classification result from the post-hoc tests based on either the muscular synergy or postural synergies as shown in Table 13. There was no tendency to be affected by the weight or size of the object, either. Nonetheless, each synergy divided the grasp into some groups.

The postural synergy 1 divided the objects according to the flexion degree of all MCPs and PIPs. The grasp #5 (ring grasp) required the hands more extended than others, followed by the grasp #1, #2, #3, #4, #6, #13, #14 and #15. Hands were little more flexed for #7, #8 and #9. The participants flexed most for grasp #12 (palmer).

The postural synergy 2 also divided the grasp into six groups with differing the details. The synergy 2 which extends thumb with flexing PIPs and extending MCPs or vice versa; the grasp #9 (power disk) and #4 (large diameter) were closed to a thumb up gesture. The grasp #1, #2, #3, #5, #6, #8 and #10 were not significantly different in terms of postural synergy 2. The grasp #7 (medium wrap) and #11 (lateral) were

statistically identical with #15 (smartphone) and #12 (palmer), respectively. The grasp #14 (parallel extension) and #13 (extension type) did not belong to any group of grasps.

The postural synergy 3 which was related to thumb joints worked with extending MCPs and flexing PIP, like claw was a criterion to distinguish the grasps, too. The most claw-like grasp was the grasp #9 (power disk) followed by #11 (lateral). Grasp #10 (hook) and #12 (palmer) were the next claw-like grasps. Grasp #1, #2, #3, #4, #5, #6, #7 and #15 were significantly same in terms of postural synergy 3. A group of grasps, #14 (parallel extension) and #13 (extension type), was the least claw-like grasp group with the lowest score of this synergy.

The muscular synergy 1 divided the objects into four groups. The grasp #9 (power disk) required most muscular synergy 1 and grasp #12 (palmer) was following it. The grasp #8 (adducted thumb), #11 (lateral) and #15 (smartphone) showed the least amount of the synergy. Rest of the grasps belonged to the same group in terms of the synergy 1.

The muscular synergy 2 sectioned the objects to three groups. The first group of which members was the grasp #12 (palmer) and #14 (parallel extension). This group required extending thumb and index finger during grasping the objects. The rest objects were the members of the last group and required grasping with flexed fingers and thumb. The grasp #5 (ring), #9 (power disk) and #13 (extension type) were not significantly different in terms of the muscular synergy 2. Rest ten grasps were also assigned to a group which required more thumb activation than other grasps.

To sum up the result from each of the postural synergy, the grasp #1, #2, #3 and #6 were defined as the same posture type of grasp (P1) and the grasp #7 and #15 were the same posture type (P4). Others belonged to their own posture types. Figure 26 shows the location of each grasp in a 3D plot. In the case of grasp type classified by both muscle synergies, the grasp #1, #2, #3, #4, #6, #7 and #10 were grouped together (M1), and so were #5 and #13 (M2). The grasp #8, #11 and #15 belonged to the same group (M3) and #12 had its own grasp type, as well as #14. The illustration of this result is shown in Figure 27.

Considering three synergies related to joint angles and two synergies of EMG altogether, 15 grasps could be defined as a total of 12 identical types of grasp. The sphere types of grasp, the grasp #1 (sphere 4-fingers), #2 (tripod), #3 (quadpod), and #6 (precision disk), were the same grasp type considering all synergies listed above. In other words, the grasps required the same muscular synergies and postural synergies even if they utilized different fingers and even grasped different objects. Other grasps were independent of each other and distinctive.

This result revealed that the grasps did not comply with the existing criteria when the grasp was explained by the muscular and postural synergies. The conventional grasp types which are the precision grasp and the power grasp were not the classification standard.

Table 11. The result of ANOVA for muscular synergies

		Sum of Squares	df	Mean square	F	Significance
Muscular synergy 1	Between Groups	1620.896	14	115.778	123.331	0.000
	Within Groups	6374.180	6790	0.939		
	Total	7995.075	6804			
Muscular synergy 2	Between Groups	1156.612	14	82.615	207.129	0.000
	Within Groups	2708.248	6790	0.399		
	Total	3864.860	6804			

Table 12. The result of ANOVA for postural synergies

		Sum of Squares	df	Mean square	F	Significance
Postural synergy 1	Between Groups	31138.337	14	2224.167	1099.933	0.000
	Within Groups	16732.816	8275	2.022		
	Total	47871.153	8289			
Postural synergy 2	Between Groups	3671.705	14	262.265	307.342	0.000
	Within Groups	7061.322	8275	0.853		
	Total	10733.027	8289			
Postural synergy 3	Between Groups	9210.151	14	657.868	804.982	0.000
	Within Groups	6762.706	8275	0.817		
	Total	15972.857	8289			

Table 13. The results of the post-hoc tests for all grasps

Grasp no.	Types	Thumb location	Object type	Weight (g)	Size (mm)	Shapes	PS* 1	PS* 2	PS* 3	Description (postural)	Type (postural)	MS** 1	MS** 2	Description (muscular)	Type (muscular)	Grasp type
1	Power	Abducted	Tennis ball	40	60	Sphere	5	b	C	Big egg	P1	3	c	Finger flex	M1	G1
2	Precision	Abducted	Pingpong ball	5	25	Sphere	5	b	C	Big egg	P1	3	c	Finger flex	M1	G1
3	Precision	Abducted	Pingpong ball	5	25	Sphere	5	b	C	Big egg	P1	3	c	Finger flex	M1	G1
4	Power	Abducted	Bottle	150	50	Cylinder	5	a	C	Big thumb up	P2	3	c	Finger flex	M1	G2
5	Power	Abducted	Bottle	150	50	Cylinder	6	b	C	Okay	P3	3	b	Finger flex	M2	G3
6	Precision	Abducted	Bottle lid	20	50	Disk	5	b	C	Big egg	P1	3	c	Finger flex	M1	G1
7	Power	Abducted	Thin bottle	140	40	Cylinder	5	c	C	Small egg	P4	3	c	Finger flex	M1	G4
8	Power	Adducted	Thin bottle	140	40	Cylinder	4	b	B	Small thumb up	P5	4	c	Finger flex	M3	G5
9	Power	Abducted	Big lid	150	100	Disk	4	a	F	Claw	P6	1	b	Thumb action with finger ext	M4	G6
10	Power	Adducted	Dumbbell	1000	15	Cylinder	4	b	D	Hook	P7	3	c	Neutral	M1	G7

11	Intermediate	Adducted	Battery	52	7	Thin rectangular parallelepiped	3	d	E	Pinch	P8	4	c	Finger flex	M3	G8
12	Power	Adducted	Plate	400		Big disk	2	d	D	Fist	P9	2	a	Neutral	M5	G9
13	Power	Abducted	Plate	400		Big disk	1	e	A	Thumb clip	P10	3	b	Thumb action with finger flex	M2	G10
14	Precision	Adducted	Booklet	90	7	Thin rectangular parallelepiped	5	f	A	Thumb opposed to palm	P11	3	a	Finger flex	M6	G11
15	N/A		Smart-phone	150		Thin rectangular parallelepiped	5	c	C	Small egg	P4	4	c	Finger flex	M3	G12

**PS: Postural synergy, **MS: Muscular synergy*

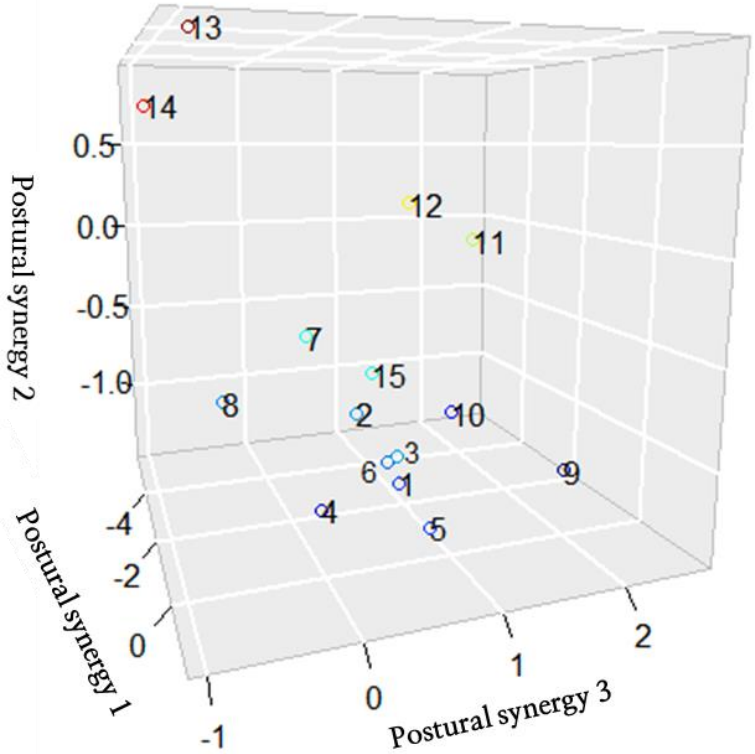


Figure 26. The 3D scatter plot of the grasps

in terms of the postural synergy 1, 2 and 3

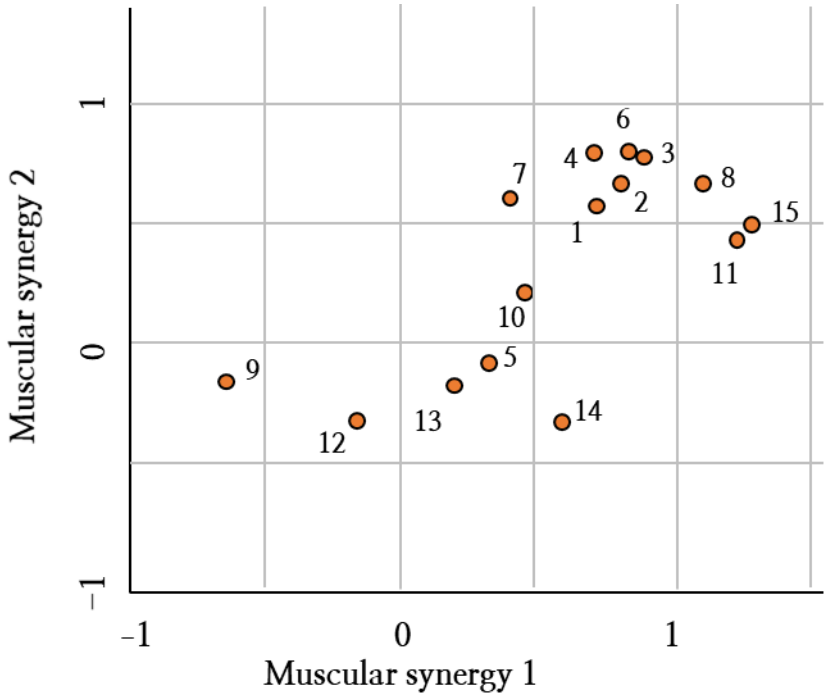


Figure 27. The 2D scatter plot of the grasps

in terms of the muscular synergy 1 and 2

5.2.2 Identifying the grasp for the touchscreen device

The smartphone grasp showed most similar grasp pattern with grasping a small bottle of which diameter (grasp #7) was 40mm with fingers and thumb opposed to the palm in terms of the postural synergies. Statistically, the touchscreen device was significantly different with other objects.

Besides, the smartphone grasp was similar to lateral grip type in which thumb pad opposed to the side of the index finger (grasp #11) considering both two muscular synergies. Another grasp similar to the smartphone grasp was the grasp pattern with grasping a small bottle (grasp #8) of which diameter was 40mm with fingers opposed to the palm, but not flexing thumb.

Since the grasp type determined by the postural synergies and the one by the muscular synergies were mutually exclusive, the smartphone was statistically distinguished from all other grasps. This indicates that the smartphone grasp is not allocated to any other class of the existing taxonomies and has a totally different property in grasping.

5.3 Grasp pattern comparison among groups

The results of ANOVA and post-hoc tests indicate that all groups were different in each postural or muscular synergy for every grasp type. In the case of smartphone grasp, hand group 3 was significantly different compared to other groups which had a larger hand for postural synergy 1. In the case of other postural synergies, all groups were distinguished. This means that different types of strategies in grasping are taken depending on the hand type. With little variation, other grasps showed similar patterns; in some cases, hand groups were different from each other, but in other cases, the groups were divided into two to one.

5.4 Conclusions and Discussion

Understanding the hand grasp pattern has important implications for the basic research of hand tool design, rehabilitation, robotics or prosthetic hand design. Instead of considering all degrees of freedom independently, human hand grasp can be explained and reproduced more easily with the postural and muscular synergies.

The purpose of this chapter was to revise current grasp taxonomy and to add the smartphone grasp to the existing taxonomy. In order to achieve this goal, the followings were accomplished: 1) identifying the grasp in terms of the synergies for the existing grasp types, 2) allocating the grasp for a smartphone to the existing taxonomy and 3) figuring out the difference among the hand groups defined from Chapter 3.

Having with the synergies of muscle and posture, the grasps were compared to each other. As a result, it was found that the muscular and postural synergies required to grasp a smartphone were significantly different from those of all other objects in the existing taxonomy. Among them, the smartphone grasp posture was similar to wrapping the small bottle of which diameter was 40mm with the fingers and the thumb. This means that although the shape of the smartphone is likely to be a thin rectangular parallelepiped, the user grasps the device as it is a cylinder type of object. In this case, there is an empty space between the hand and the device due to the discordance of shape. This may lead to contacting the edge of the device and increase pressure on the contact area, resulting in an uncomfortable grasp [139]. The muscle activity required for smartphone grasp was analogous to one for the grasp with small and light objects

without thumb actions. The result was caused by the situation where the participants gripped the device without thumb operation.

According to the result, it can be inferred that weight is not the independent influencer in classifying the type of grasp. The smartphone and the larger bottle had the same weight, but the results were quite different due to their shape and consequently the afforded grip posture. Moreover, even if the grip postures are different, the same object can belong to another group. For example, the thumb adduction-abduction separated the grasp type even for the same bottle.

Based on this result, it can be also inferred that the precision grasp and the power grasp which were the determinant of classifying grasps as the existing taxonomy system suggests did not distinguish the grasps when muscular and postural synergies are considered.

In the case of muscle activity, the smartphone grasp required similar patterns of the muscle synergies for the lateral grasp of a thin rectangular parallelepiped object of which weight and length were 52g and 7mm, respectively and the ring grasp of a small cylinder with a diameter of 40mm and a weight of 140g. Considering both synergies, it was found that the smartphone grasp was a distinct grasp type from other grasps; the grasps which showed similar postural patterns to the smartphone grasp showed different muscular patterns and vice versa.

Although most grasps had their own grasp style, the grasp type of spherical objects and a small disk were identical in terms of both synergies. To grasp those objects required similar muscle use patterns and hand postures bending four fingers and a

thumb halfway and empty space inside of the hand. These grasps required different contact composition of fingers, for example, the tripod grasp and the quadpod grasp, but these grasps eventually set the same configuration of fingers according to the muscular and postural synergy data.

However, a primary task of a smartphone can be considered to be operating the device rather than simply holding it during tasks. In addition, various interactions between the human hand and the touchscreen device occur during the operation, and the detailed hand grasp patterns are also affected by the interactions. Therefore, the grasp pattern of the smartphone grasp may be different from that of simply grasping the device according to interaction methods and the corresponding touch area. In this chapter, however, the grasp patterns during interaction were not included and analyzed for the handheld touchscreen device. In the following chapter, it would be meaningful to conduct the grasp classification according to each interaction type.

Chapter 6. Operational Analysis on Hand

The smartphone is one of the most frequently used devices. However, the uniformed device does not always fit for every user which can lead to an uncomfortable use.

As an everyday product, some problems leading to an uncomfortable use or possible disease may occur due to the sustained use of the smartphone. Overuse with poorly designed smartphones or interaction can cause repetitive strain injuries (RSI), such as De Quervain's syndrome, carpal tunnel syndrome and trigger finger syndrome. One study concluded that overuse of touchscreen device can enlarge the median nerve, cause pain in the thumb, and finally decrease pinch strength and hand functions based on the result of taking ultrasonography data on flexor pollicis longus (FPL) tendon and median nerve [28].

Researches have been actively conducted on the use of smartphones to prevent problems or improve usability. The main topics in the research area of human factor are touch interaction, thumb envelope, form factors, size or layout of soft keys, performance in terms of speed and accuracy, typing method, user comfort including fatigue, the effect of thumb size, and force/pressure. Since the smartphones are operated by thumbs, thumb-related studies have also become the mainstream.

However, not many studies were done on grasp as reviewed in Chapter 2. For example, Huy et al. [107] tried to find the comfortable and maximum range of fingers by focusing on Back-of-Device touch interface with four different sizes of

smartphones. In this study, the location of MCPs of fingers was recorded by a 3D motion capture system, but the data was used to define a comfortable area without constructing the grasp posture. Pelosi [140] investigated mobile phone grip when answering the phone and texting a message under various environmental conditions, but the study focused on the task and did not consider hand postures. To keep the stable operations of a smartphone, the grasp for each type of task should be considered simultaneously. Also, they did not explain hand motions in the aspect of motor control, which coordinates muscles and joint angles.

This chapter aims to investigate the effect of hand type and task level (tapping location of tapping task and drag direction of dragging task) on the smartphone grasp and the thumb operation in terms of muscular synergies and postural synergies same as the previous chapter. It was analyzed to understand both thumb operation and grasps during using smartphone more deeply.

To inquire this topic, an experiment was conducted, and two tasks were involved in the experiment: the drag and tap interaction which were the most commonly used interaction for the touchscreen devices. Several levels which were characterized by the location or direction were selected for each task. In the experiment for this chapter, EMG and joint angle will be measured to analyze the use behavior of the touchscreen device. During performing the tapping and dragging tasks, the hand grasps will be investigated in addition to the thumb operations.

After the experiment, the results were compared by hand types defined in Chapter 3. In the following section, the results will be analyzed considering two factors, the

task levels and hand types for each task in terms of synergies which were defined by the joint angles and muscle activities in Chapter 4. The findings of this chapter can be applied to design smartphone interaction designs.

6.1 Manual Operations Measurement

6.1.1 Experimental design

An experiment conducted in this chapter consisted with the tapping task and dragging task. For the tapping task, this experiment was designed as a two-factorial experiment to investigate the effects of hand type and location of tapping. For the dragging task, in addition to the two factors mentioned before, another factor which was the phases of dragging was included so that three-factorial design could be applied.

The tapping task included 15 levels and the tapping targets were represented as dots. The dots of same size were aligned regularly as shown in Figure 28. The levels of tapping task were numbered by a 100-digit number, from top-left (101) to bottom-right (115) and the levels of dragging task were numbered by a 200-digit number, clockwise, from SW (201) to NE (208).

In other words, the tapping experiment was full factorial design with three types of hand and 15 tapping location. The dragging task included eight directions which were east (E), west (W), south (S), north (N), south-east (SE), south-west (SW), north-east (NE) and north-west (NW). Each direction was indicated by a line with single arrows on the screen. Each dragging operation was divided into three phases, initial, middle and final or beginning, middle and ending. Thus, the dragging task was 3 (hand type) X 8 (dragging direction) X 3 (dragging phase) factorial design. The carry-over effect in which the effect gained from one experimental condition remains

to another condition was controlled by using a Latin Square method.

The stimuli were provided on the screen by playing video clips. The screen indicated where the participant asked to tap and drag with the highlighted color of dots and arrows, respectively. During the experiment, the screen was locked to prevent unintentional operations after the video clip began.

Dependent variables were the muscular and postural synergies, and independent variables were the level of each task and hand type. Other things such as a touchscreen device and environmental conditions were controlled; same as Chapter 4, the participants were allowed to grasp and operate the device with a single hand in the fixed experimental environments, for example, location, room temperature, and humidity. To prevent getting fatigue, after completing the grasping tasks in the previous experiment in Chapter 5, the participants had enough time to take a rest.

Figure 28. Tapping task (left) and dragging task (right)

6.1.2 Data analysis

In order to construct muscular and postural synergies, PCA was performed and each component became a synergy in Chapter 4. Based on the synergies, in order to inquire the main effects, ANOVA was performed to compare hand motions by hand type and to find the difference between task levels, tapping locations and the directions of dragging. Two-way and three-way ANOVA was performed to determine if there was an interaction effect between hand type and task level. As in Chapter 5, the statistical analyses were performed by running R Studio version 1.0.136 with the R packages and SPSS (IBM, version 23).

6.1.3 Procedure

Sitting in a chair, the participants were asked to keep holding their elbow angle 90 degrees during the tasks. The experiment for this chapter took 15 minutes with two breaks. Attaching a ground electrode, or called a reference electrode, on an elbow joint at which tissues were electrically neutral [141], the participants two tasks were performed in the order of tapping and dragging. For the tapping task, the participants were asked to tap the targets at 15 different positions located all over the screen. The dragging task included eight different directions (N, NE, E, SE, S, SW, W and NW). The stimulus for each task was provided as a prepared video on the screen of the device so that the interval and duration of the stimulus could be controlled. The participants were instructed to drag along the given lines and arrows. All lines were identical in length, 25 mm. The task descriptions are illustrated in Figure 28. All tasks were performed by the participants' preferred hands without controlling their grasp.

Re-grasping was allowed during the experiment. All activities of each muscle were recorded individually while the participants performed all tasks. The order of the device given to the participants was randomly chosen to eliminate order effects. Figure 29 illustrates the experiment during the tapping task.

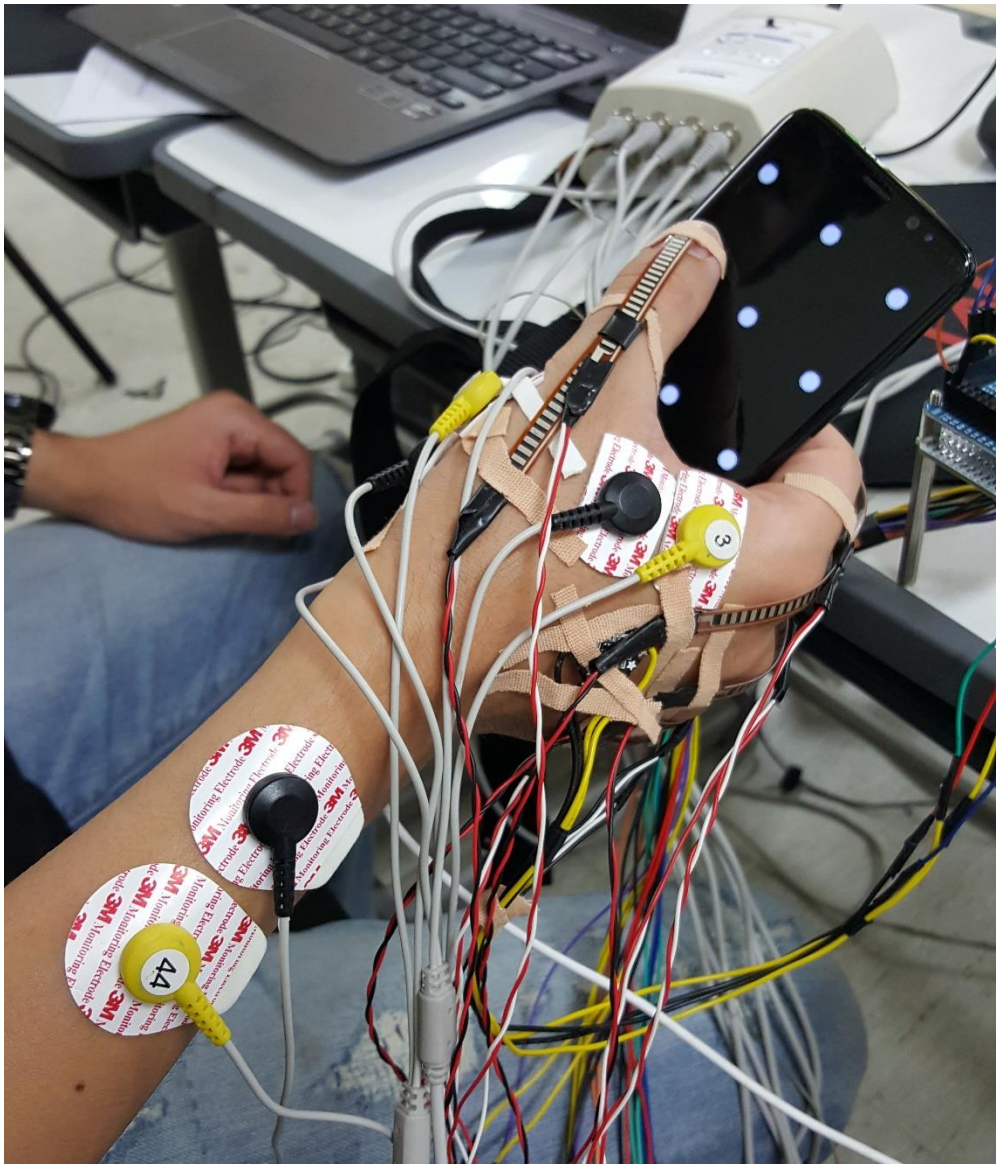


Figure 29. An illustrative example of the tapping task

6.2 Biomechanical Analysis of Operational Tasks for Touchscreen device

6.2.1 Hand motion analysis on tapping task

In order to investigate the effect of hand type and the location of tapping point (task level) on muscular activities and hand posture, two-way ANOVA tests were conducted. Table 14, Table 15, Table 16, Table 17 and Table 18 represent the results of ANOVA. According to the result of the tests, there were significant interaction effects between the task level and the hand type for all of two muscular synergies and three postural synergies. This means that the effect of the anthropometrical difference of hand differed according to the task level.

Figure 30 showed the result of post-hoc tests of patterns of the postural synergy for each hand type in the tapping task. The number in the cell denotes the section achieved the post-hoc test. The cells with same number indicate they are not significantly different in terms of the corresponding synergy. The red color indicates more positive values of postural synergies and green indicates more negative values of each postural synergy. In the case of postural synergy 1, the three hand types showed different results based on the number of sections, but the similar pattern that the synergy was more activated as the tapping point was moved from top-left to the bottom-right side was found. For hand type 3, the surface of the device was divided into eight sections in terms of postural synergy 1 and others had less numbers of sections. Hand type 3 (small hand) therefore, was more sensitive to the location of tapping location than hand type 1 (large hand with longer fingers).

The postural synergy 2 was performed similar to the first postural synergy requiring more activation at the right-bottom area. However, rest parts had different patterns among the hand types. In the case of the postural synergy 3, as illustrated in Figure 30, three hand types showed totally different patterns. Postural synergy 2 was more activated at the right side with extended PIPs. The synergy 3 showed a similar result of less activation on the right side which meant extending PIPs, too. From this, it can be inferred that postural synergy 2 and 3 compensate each other in order to maintain left-right balance. Also, all tapping levels required different combinations of the postural synergies and this indicates that the 15 locations induced different posture to tap with different motion strategies.

Same as postural synergies, muscular synergies had some noticeable patterns as found in Figure 31. In general, the muscular synergy 1 was likely to be horizontally symmetric and the muscular synergy 2 to be vertically symmetric. Also, hand type 1 activated muscle synergy 1 more to the upper-right corner, but other hand type groups more activated middle part of the right side. One possible reason for this is longer fingers of hand type 1 than other types. In contrast with the postural synergies, some area required the same muscle activities within the same hand type. For example, hand type 1 (large hand with long fingers) and type 2 (large hand with a long palm) had the location of 108 and 109, middle-right location of the screen, which required the same muscle pattern. In the case of hand type (short hand), the generated muscle synergies were same when tapping the location 106, 109 and 112, mid-right area of the screen.

Table 14. Tests of Between-Subjects Effects: Postural synergy 1 for tapping

Dependent variable: Postural synergy 1

Source	Type III Sum of squares	Degree of Freedom	Mean Square	F	Significance
Corrected model	31393.550	44	713.490	434.337	0.000
Intercept	2088.846	1	2088.846	1271.584	0.000
Level	24567.600	14	1754.829	1068.251	0.000
Group	2780.663	2	1390.332	846.364	0.000
level * group	421.300	28	15.046	9.160	0.000
Error	11942.515	7270	1.643		
Total	44559.502	7315			
Corrected total	43336.065	7314			

Table 15. Tests of Between-Subjects Effects: Postural synergy 2 for tapping

Dependent variable: Postural synergy 2

Source	Type III Sum of squares	Degree of Freedom	Mean Square	F	Significance
Corrected model	3177.577	44	72.218	86.260	0.000
Intercept	464.410	1	464.410	554.711	0.000
Level	1989.630	14	142.116	169.750	0.000
Group	577.130	2	288.565	344.674	0.000
level * group	286.842	28	10.244	12.236	0.000
Error	6086.530	7270	0.837		
Total	9638.455	7315			
Corrected total	9264.107	7314	0		

Table 16. Tests of Between-Subjects Effects: Postural synergy 3 for tapping

Dependent variable: Postural synergy 3

Source	Type III Sum of squares	Degree of Freedom	Mean Square	F	Significance
Corrected model	4851.105	44	110.252	138.918	0.000
Intercept	196.203	1	196.203	247.217	0.000
Level	3745.278	14	267.520	337.076	0.000
Group	42.409	2	21.205	26.718	0.000
level * group	636.806	28	22.743	28.656	0.000
Error	5769.829	7270	0.794		
Total	10881.215	7315			
Corrected total	10620.934	7314			

Table 17. Tests of Between-Subjects Effects: Muscular synergy 1 for tapping

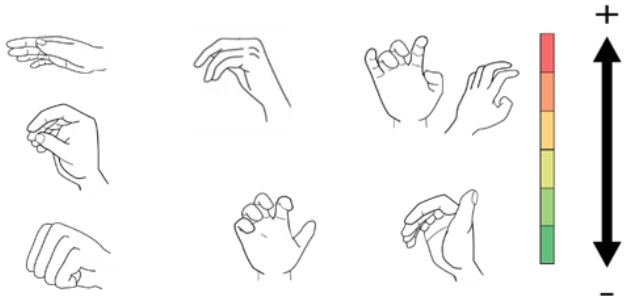
Dependent variable: Muscular synergy 1

Source	Type III Sum of squares	Degree of Freedom	Mean Square	F	Significance
Corrected model	39161.184	44	890.027	461.251	0.000
Intercept	248.797	1	248.797	128.937	0.000
Level	25049.657	14	1789.261	927.274	0.000
Group	6319.246	2	3159.623	1637.456	0.000
level * group	3537.115	28	126.326	65.467	0.000
Error	49860.664	25840	1.930		
Total	90159.816	25885			
Corrected total	89021.848	25884			

Table 18. Tests of Between-Subjects Effects: Muscular synergy 2 for tapping

Dependent variable: Muscular synergy 2

Source	Type III Sum of squares	Degree of Freedom	Mean Square	F	Significance
Corrected model	9279.982	44	210.909	181.214	0.000
Intercept	5.398	1	5.398	4.638	0.031
Level	8059.194	14	575.657	494.607	0.000
Group	66.651	2	33.326	28.634	0.000
level * group	493.436	28	17.623	15.142	0.000
Error	30074.295	25840	1.164		
Total	39383.724	25885			
Corrected total	39354.277	25884			



	Postural synergy 1			Postural synergy 2			Postural synergy 3		
Hand 1	1	2	2	2	4	4	2	1	1
	2	2	4	2	4	2	2	1	2
	2	3	4	2	4	3	3	2	2
	3	4	5	1	4	5	4	4	3
	3	4	5	2	4	5	4	5	5
Hand 2	1	2	2	1	1	2	2	2	1
	1	2	3	1	2	2	2	1	1
	2	3	4	2	3	2	1	2	3
	3	4	6	2	3	4	2	3	3
	3	5	6	1	4	4	3	4	4
Hand 3	1	2	2	1	3	3	6	2	1
	1	3	5	2	3	2	4	1	2
	2	5	7	2	3	3	4	3	3
	4	6	8	2	4	4	5	5	5
	5	7	8	2	3	4	5	5	6

Figure 30. Postural synergies pattern for each hand type in tapping task

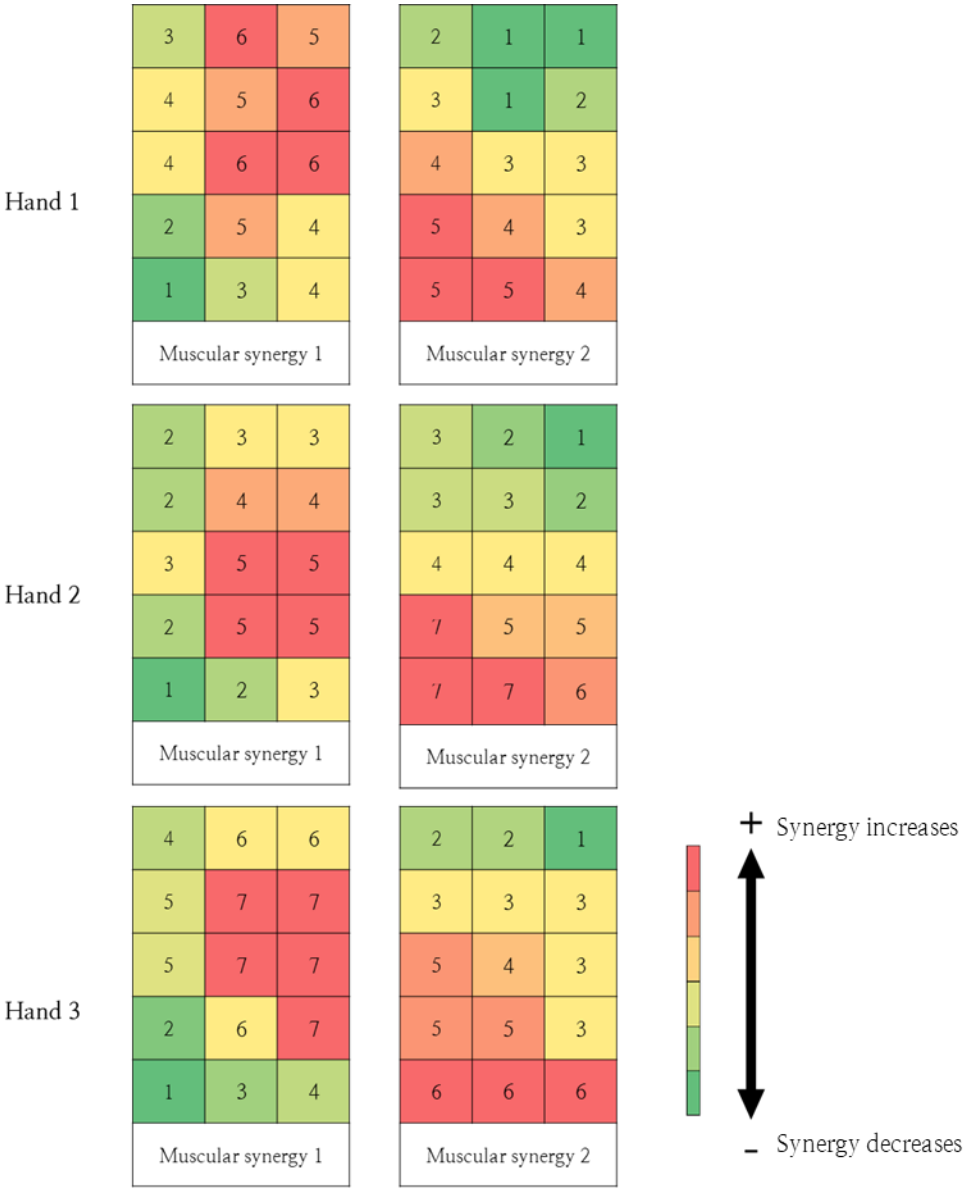


Figure 31. Muscular synergies pattern for each hand type in tapping task

Figure 32 is the scatter plot of muscular synergy 1 and 2 and the numbers indicate the location of tapping. The tapping location numbered 113 was the most challenging and distinguishable point in average as shown in the figure; this point required most muscle activities of both muscle synergies. In the case of postural synergies, tapping location numbered 101 and 115 were the most extreme points as illustrated in Figure 33. The fingers for tapping 115 required all postural synergies in the greatest positive direction. The points of 101 showed similar extreme patterns with the opposite direction of synergies 1 and 3.

Hand tilting postures were affected by hand type, too. The result from hand type 1 and 3 indicates that the wrist interacted as the tapping location changed to keep balance as indicated in Figure 34. The numbers represent groups separated by the result of post-hoc tests on the degrees to which the x-, y- and z-axis are inclined for each hand type. The x-axis was aligned along the metacarpal bone of middle finger and the three axes were pair-wise perpendicular. This means that if the hand is placed on the floor, the values of tilting degrees z-axis will be the greatest in positive way and others will be zero or neutral. The Hand type 1 and 3 took different tilting strategies during tapping the device, especially, in controlling the y-axis. The screen was separated by the tilt angles for each axis. The borderline of separation shifted according the hand size. Moreover, except for 115 level, the hand type 2 did not twist the wrist. Among the hand types, hand type 2 showed most stable performance during the tapping tasks.

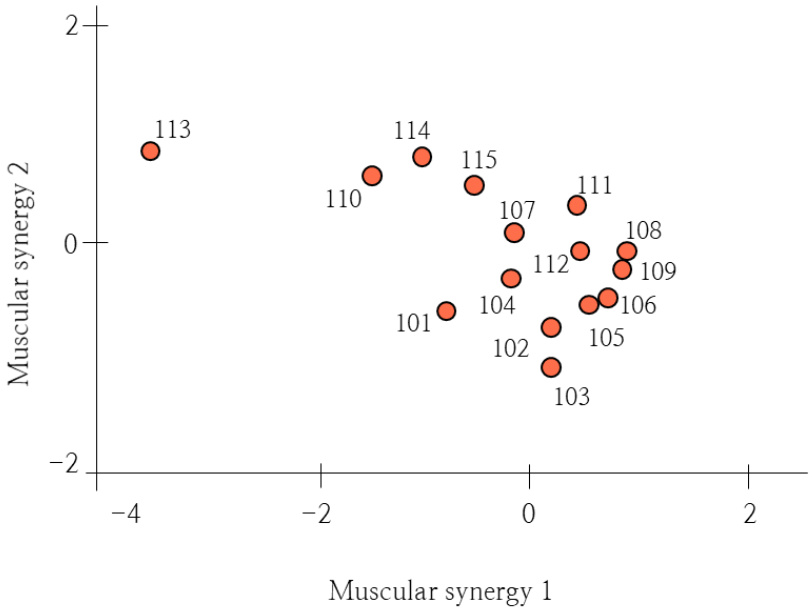


Figure 32. A 2D scatter plot of the tapping location in terms of muscular synergies

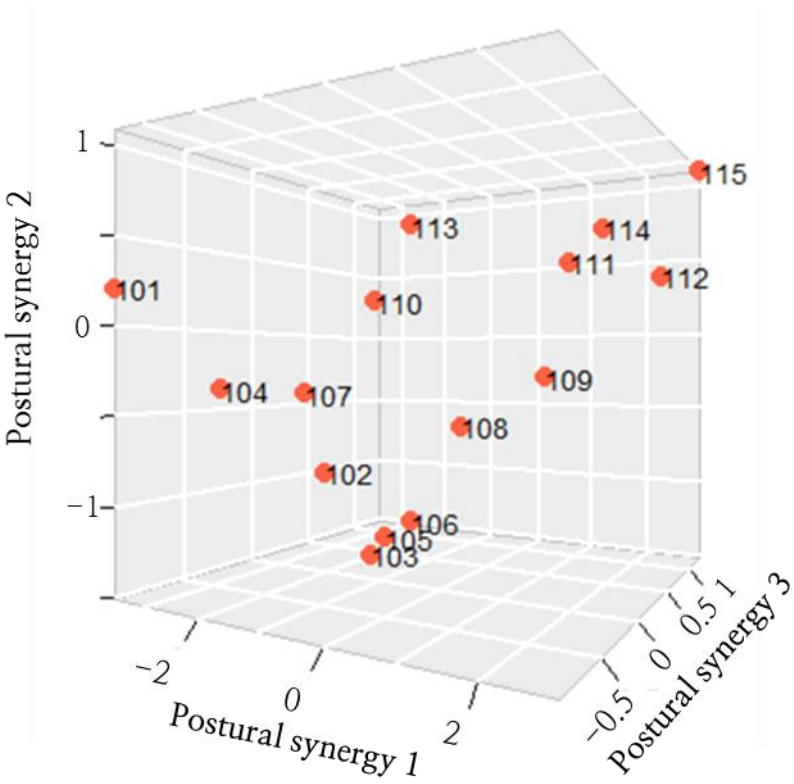


Figure 33. A 3D scatter plot of the tapping location in terms of postural synergies

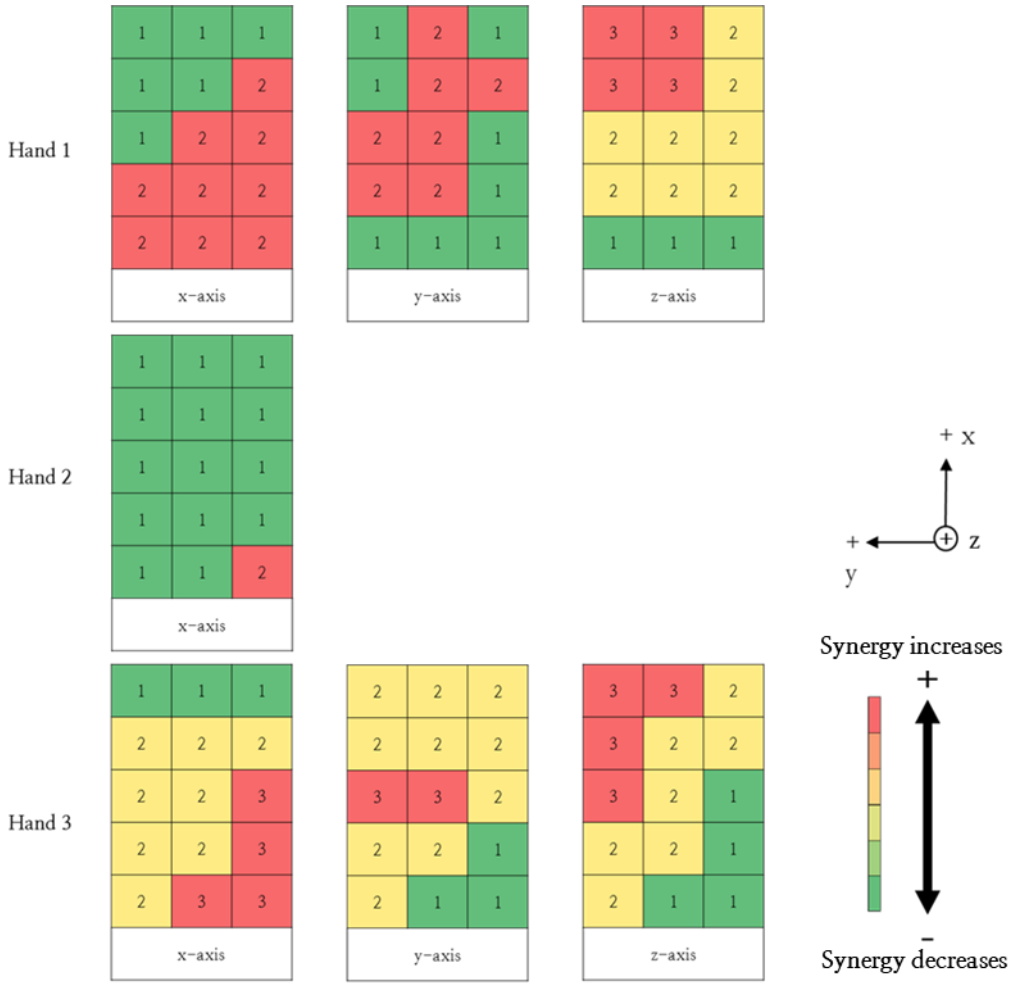


Figure 34. Hand tilting for each hand type during the tapping task

6.2.2 Hand motion analysis on the dragging task

In order to investigate the effect of hand type and the direction of dragging direction (task level) considering dragging phase (beginning, middle and ending) on muscular activities and hand posture, three-way ANOVA tests were conducted to find main effects, as well as interaction effects. The results were listed in Table 19, Table 20, Table 21, Table 22, and Table 23. According to the result of the tests, there was a significant interaction effect on task level, dragging phase and hand type for all of two muscular synergies and three postural synergies. This means that the three factors were interacted so that considering only or two factors may not be meaningful.

In the case of postural synergies, two opposite directions, for example, task level 201(SW) and 205 (NE), did not share the exact same path but showed the similar pattern on the graph if each type was observed separately as shown in Figure 35, Figure 36 and Figure 37. Also, as shown in Figure 38 and Figure 39, the dragging directions which shared the same dragging path but with the opposite way were represented by two parallel lines. For most dragging directions, the rate of change of postural synergies between the middle-final phases for hand type 1 (large hand with long fingers) was larger than the one between the initial-middle phases indicating the thumb movement became faster. The hand type 2 (large hand with longer palm) kept a relatively constant speed of thumb movement but got little faster at the second half. On the other hand, the hand type 3 (small hand), in general, the thumbs got slower as the phases progressed. The dragging levels moved from top to bottom of which directions were SW(201), SE(207) and S(208) shared similar movement pattern, so did the dragging from bottom to top, NW(203), N(204) and NE(205). During

dragging W(202) and E(206), postural synergy 1 did not change. This is presumably due to the direction demanding thumb abduction not involved in this dissertation.

The eight directions of the dragging task were grouped differently for all postural and muscular synergies combined by hand type. Figure 40 and Figure 41 provide the result of the post-hoc tests. Also, according the plots, Figure 42 and Figure 43, there was no tendency of dragging direction found even the directions were adjacent or opposed in the direction for both muscular and postural synergies.

Contrary to the tapping task, muscular synergies showed similar patterns with the same directions. Figure 44 and Figure 45 illustrate this trend. The strategy of recruiting muscular synergies was divided into two parts based on the vertical line (S and N direction). As shown in Figure 46, 201, 202 and 203 required to activate more muscular synergy 1 as thumb moved. On the other hand, 205, 206 and 207 recruited muscular synergy 2 for the dragging tasks. 204 and 208 did not make a change in activating both synergies during dragging; rather, the change was not linear. The reciprocations were not shared the path, recruitment of two muscular synergies, and this infers that moving opposite directions take different movement strategies. Figure 46 shows the path of the drag in terms of the postural synergies. Except 201, 202 and 203 directions, the value of postural synergies did not much change from the initial to the final phase of the drag. The drags which shared same path with the opposite directions were paired but not match perfectly in the graph. This indicates that the direction affects the strategy in motion.

Table 19. Tests of Between-Subjects Effects: Postural synergy 1 for dragging

Dependent variable: Postural synergy 1

Source	Type III Sum of squares	Degree of Freedom	Mean Square	F	Significance
Corrected model	4213.069	71	59.339	35.527	0.000
Intercept	1142.771	1	1142.771	684.186	0.000
Drag direction	1040.735	7	148.676	89.014	0.000
Hand type	1833.751	2	916.875	548.941	0.000
Phase	3.830	2	1.915	1.147	0.318
Hand type * Drag direction	88.971	14	6.355	3.805	0.000
Hand type * Phase	1023.371	14	73.098	43.764	0.000
Drag direction * Phase	3.149	4	0.787	0.471	0.757
Hand type * Drag direction * Phase	106.916	28	3.818	2.286	0.000
Error	6624.262	3966	1.670		
Total	12895.215	4038			
Corrected total	10837.331	4037			

Table 20. Tests of Between-Subjects Effects: Postural synergy 2 for dragging

Dependent variable: Postural synergy 2

Source	Type III Sum of squares	Degree of Freedom	Mean Square	F	Significance
Corrected model	1503.225	71	21.172	23.135	0.000
Intercept	2109.248	1	2109.248	2304.774	0.000
Drag direction	189.065	7	27.009	29.513	0.000
Hand type	977.908	2	488.954	534.280	0.000
Phase	2.580	2	1.290	1.409	0.244
Hand type * Drag direction	56.354	14	4.025	4.398	0.000
Hand type * Phase	124.152	14	8.868	9.690	0.000
Drag direction * Phase	2.761	4	0.690	0.754	0.555
Hand type * Drag direction * Phase	43.701	28	1.561	1.705	0.012
Error	3629.544	3966	0.915		
Total	7404.035	4038			
Corrected total	5132.768	4037			

Table 21. Tests of Between-Subjects Effects: Postural synergy 3 for dragging

Dependent variable: Postural synergy 3

Source	Type III Sum of squares	Degree of Freedom	Mean Square	F	Significance
Corrected model	813.395	71	11.456	14.475	0.000
Intercept	2.591	1	2.591	3.274	0.070
Drag direction	120.874	7	17.268	21.818	0.000
Hand type	107.126	2	53.563	67.678	0.000
Phase	0.468	2	0.234	0.295	0.744
Hand type * Drag direction	22.229	14	1.588	2.006	0.014
Hand type * Phase	491.331	14	35.095	44.343	0.000
Drag direction * Phase	5.056	4	1.264	1.597	0.172
Hand type * Drag direction * Phase	68.766	28	2.456	3.103	0.000
Error	3138.855	3966	0.791		
Total	3974.887	4038			
Corrected total	3952.250	4037			

Table 22. Tests of Between-Subjects Effects: Muscular synergy 1 for dragging

Dependent variable: Muscular synergy 1

Source	Type III Sum of squares	Degree of Freedom	Mean Square	F	Significance
Corrected model	4242.444	71	59.753	53.152	0.000
Intercept	472.273	1	472.273	420.101	0.000
Drag direction	1423.940	7	203.420	180.948	0.000
Hand type	1136.538	2	568.269	505.492	0.000
Phase	470.972	2	235.486	209.472	0.000
Hand type * Drag direction	428.029	14	30.573	27.196	0.000
Hand type * Phase	680.059	14	48.576	43.209	0.000
Drag direction * Phase	215.400	4	53.850	47.901	0.000
Hand type * Drag direction * Phase	119.151	28	4.255	3.785	0.000
Error	15789.248	14045	1.124		
Total	20191.027	14117			
Corrected total	20031.693	14116			

Table 23. Tests of Between-Subjects Effects: Muscular synergy 2 for dragging

Dependent variable: Muscular synergy 2

Source	Type III Sum of squares	Degree of Freedom	Mean Square	F	Significance
Corrected model	1671.574	71	23.543	22.767	0.000
Intercept	269.878	1	269.878	260.981	0.000
Drag direction	881.208	7	125.887	121.737	0.000
Hand type	58.411	2	29.206	28.243	0.000
Phase	1.842	2	0.921	0.890	0.410
Hand type * Drag direction	312.311	14	22.308	21.573	0.000
Hand type * Phase	436.257	14	31.161	30.134	0.000
Drag direction * Phase	40.865	4	10.216	9.879	0.000
Hand type * Drag direction * Phase	80.326	28	2.869	2.774	0.000
Error	14523.804	14045	1.034		
Total	16457.899	14117			
Corrected total	16195.378	14116			

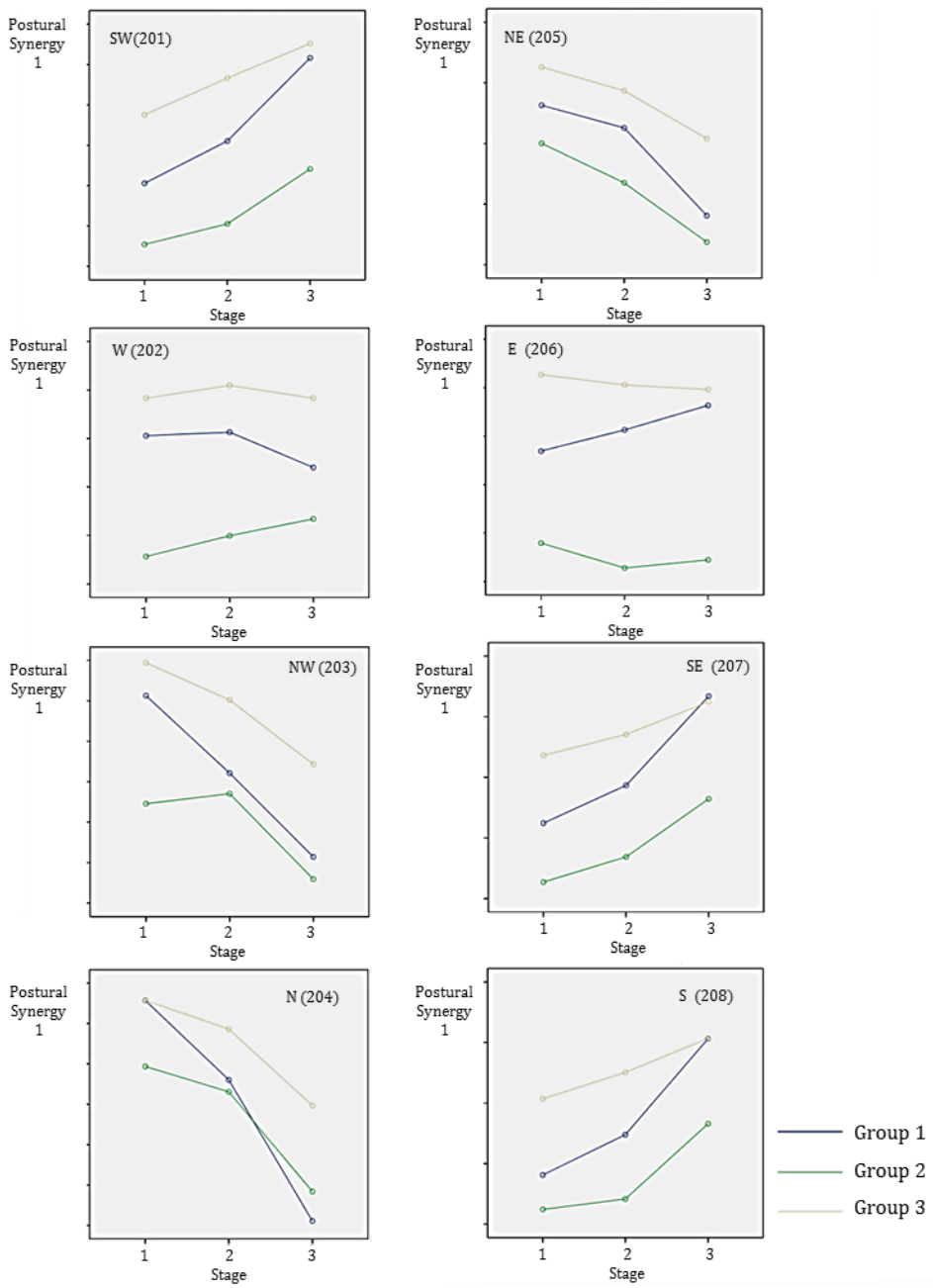


Figure 35. The postural synergy 1 for the dragging during three phases

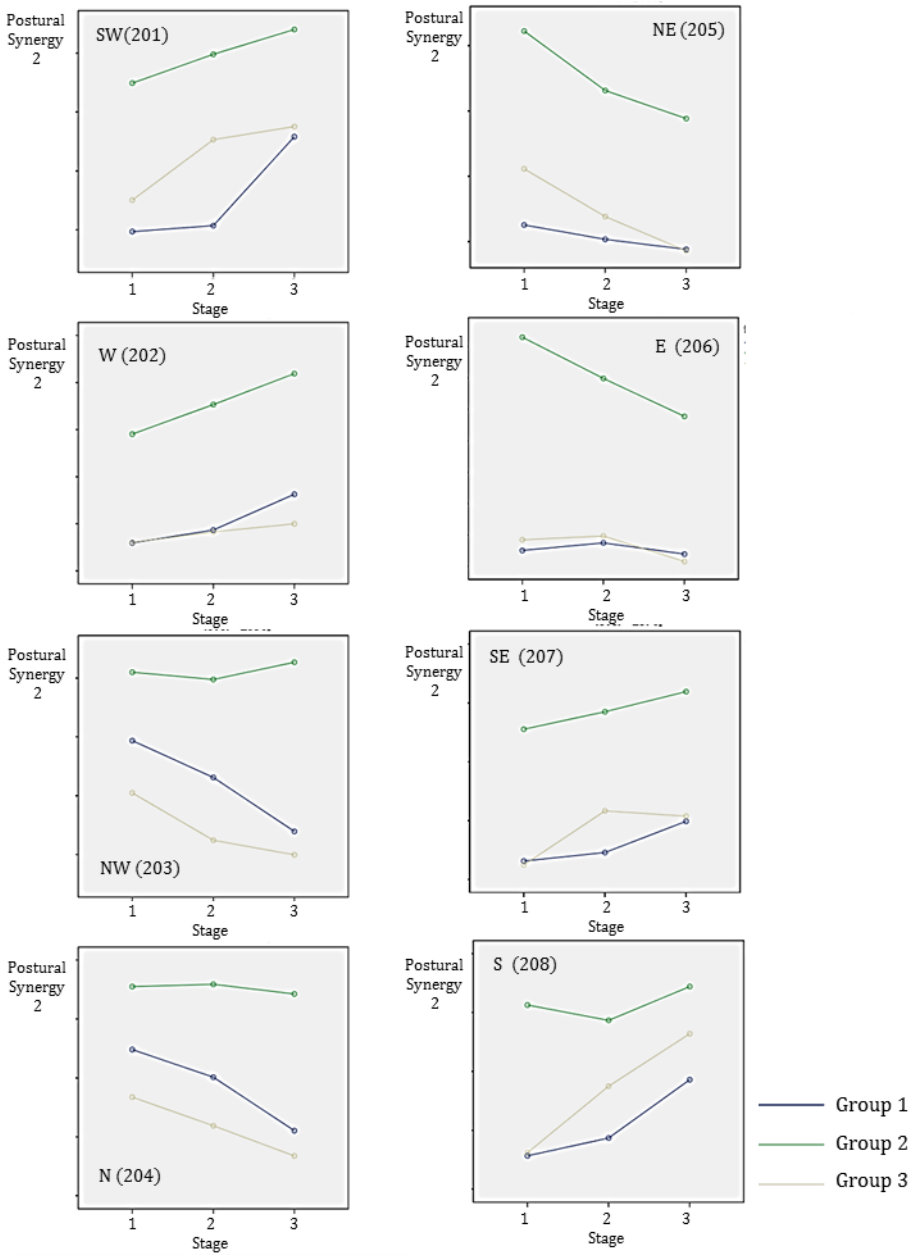


Figure 36. The postural synergy 2 for dragging during three phases

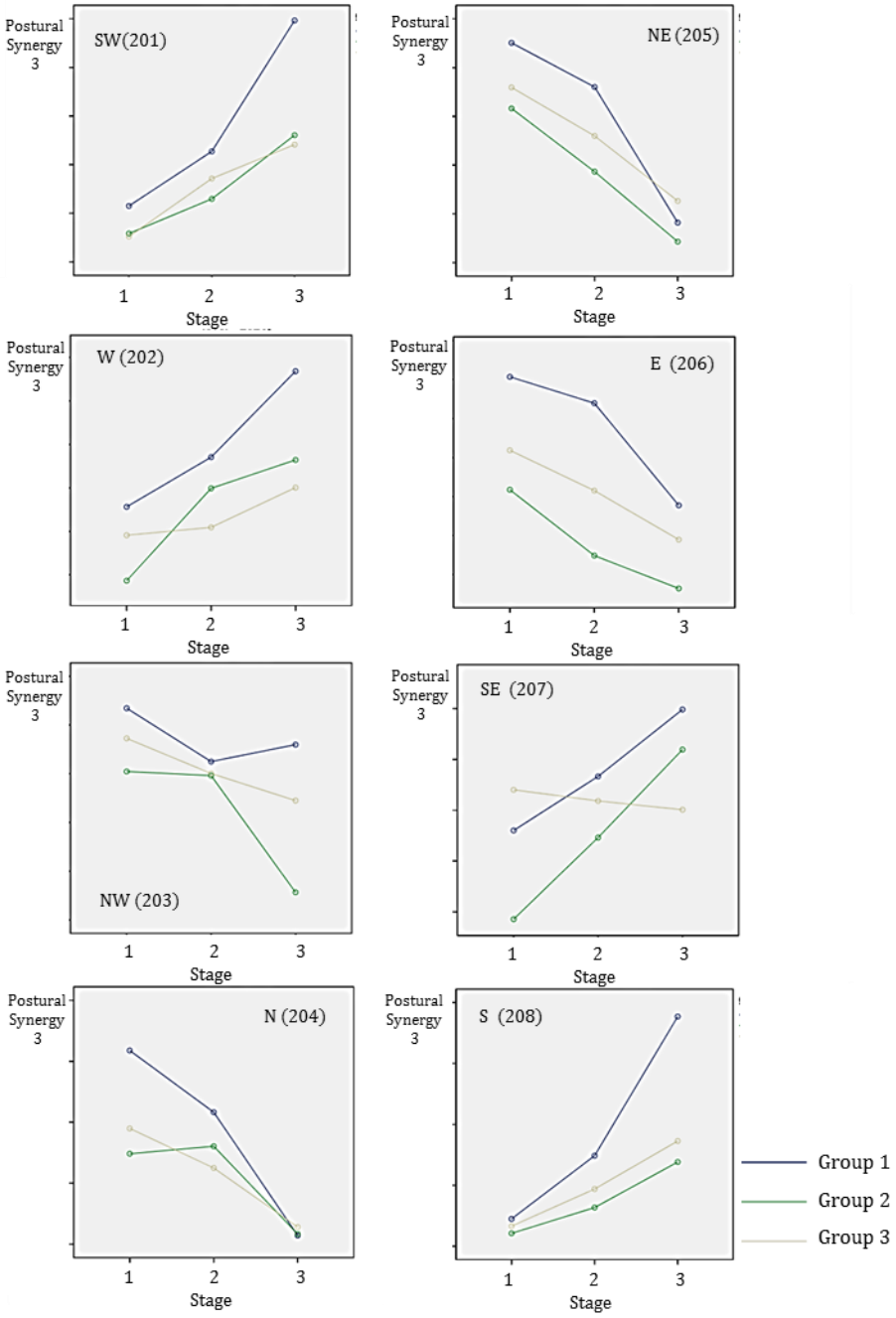


Figure 37. The postural synergy 3 for dragging during three phases

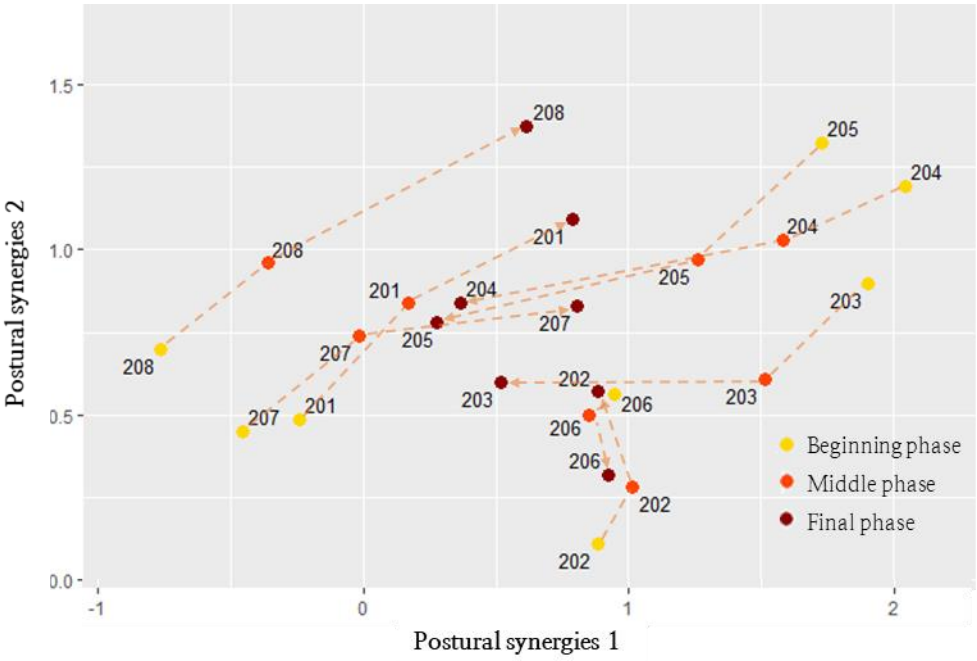


Figure 38. The 2D scatter plot of postural synergies 1 and 2 for three drag phases

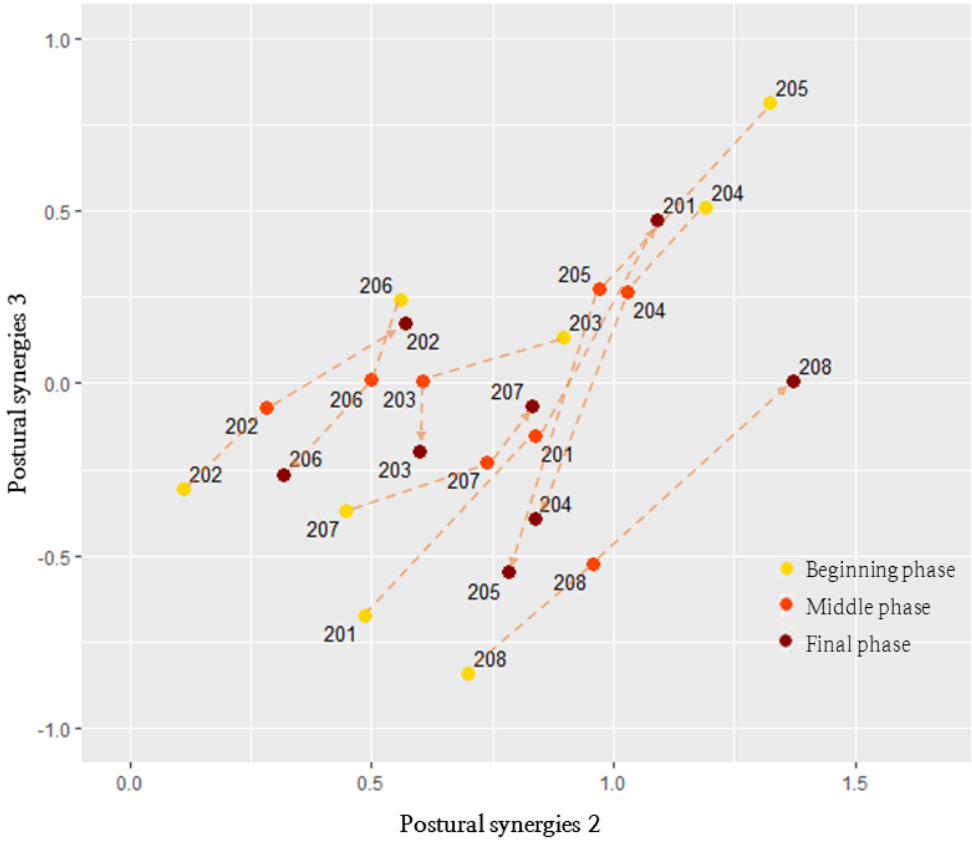


Figure 39. The 2D scatter plot of postural synergies 2 and 3 for three drag phases

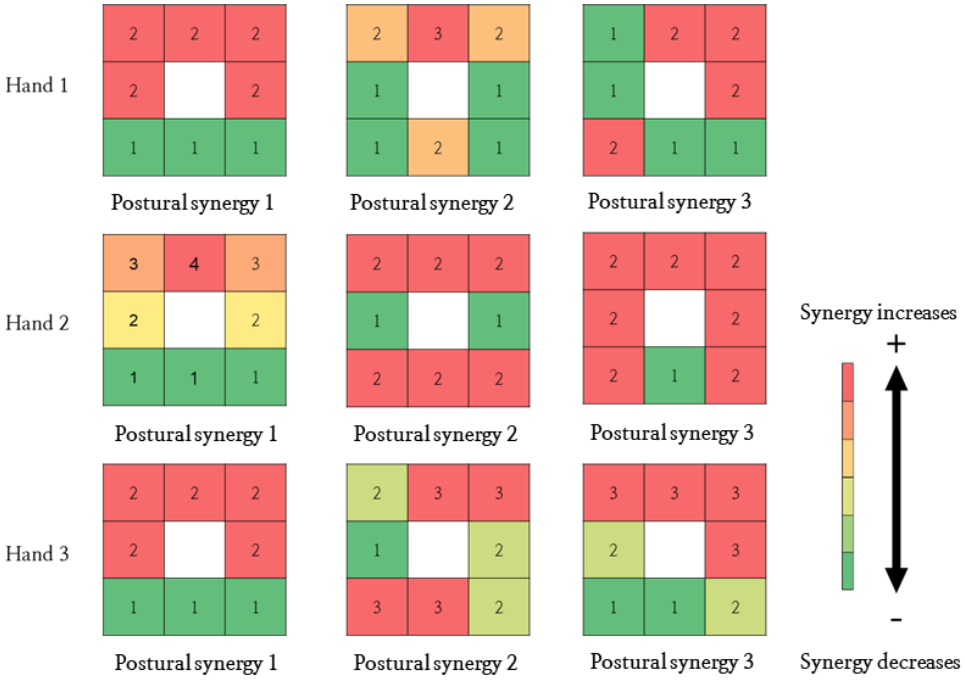


Figure 40. Postural synergies pattern for each hand type in dragging task

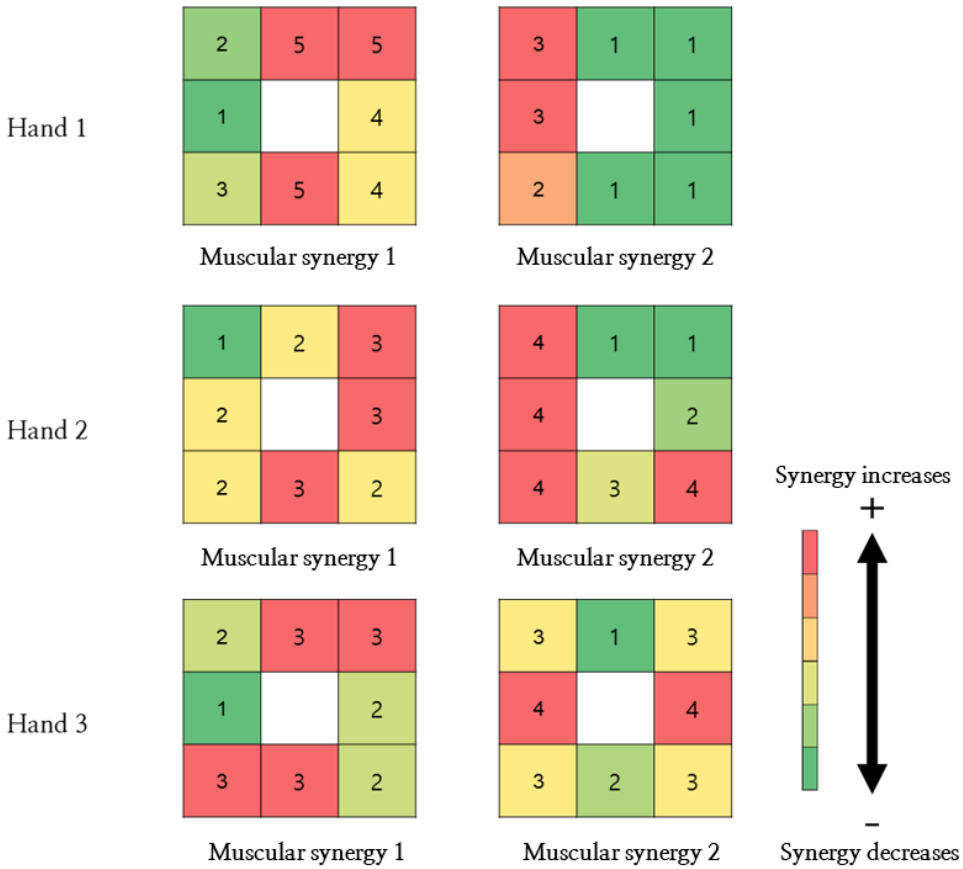


Figure 41. Muscular synergies pattern for each hand type in dragging task

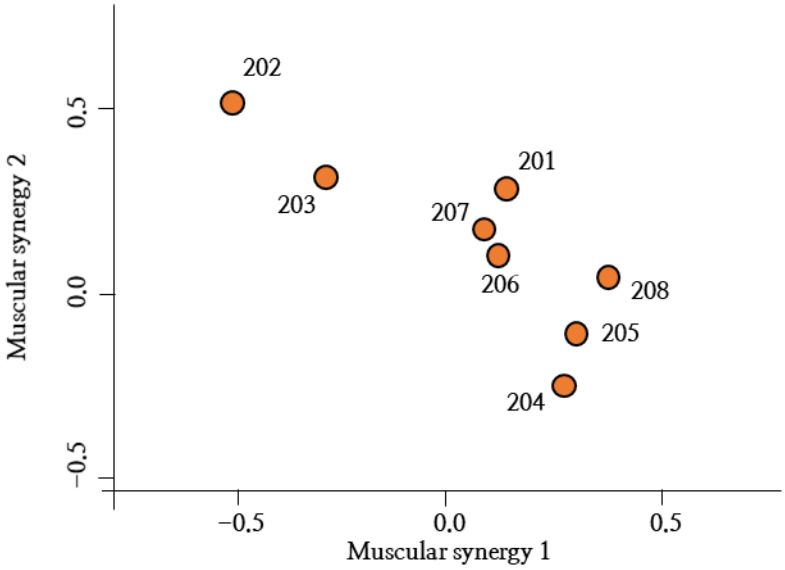


Figure 42. The 2D scatter plot of muscular synergies for eight levels of the dragging tasks

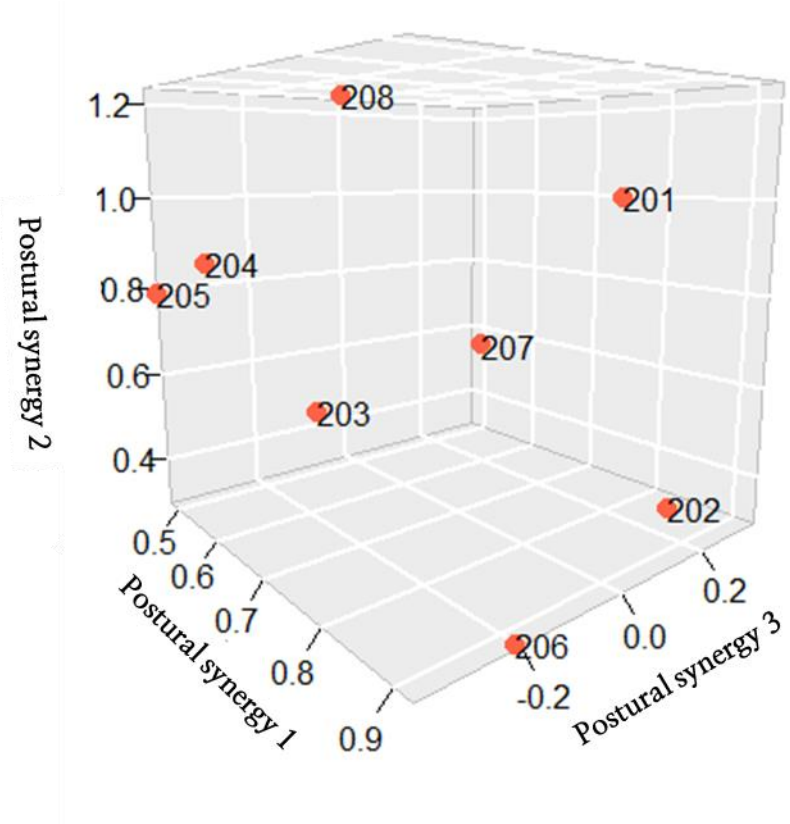


Figure 43. The 3D scatter plot of postural synergies for eight levels of the dragging tasks

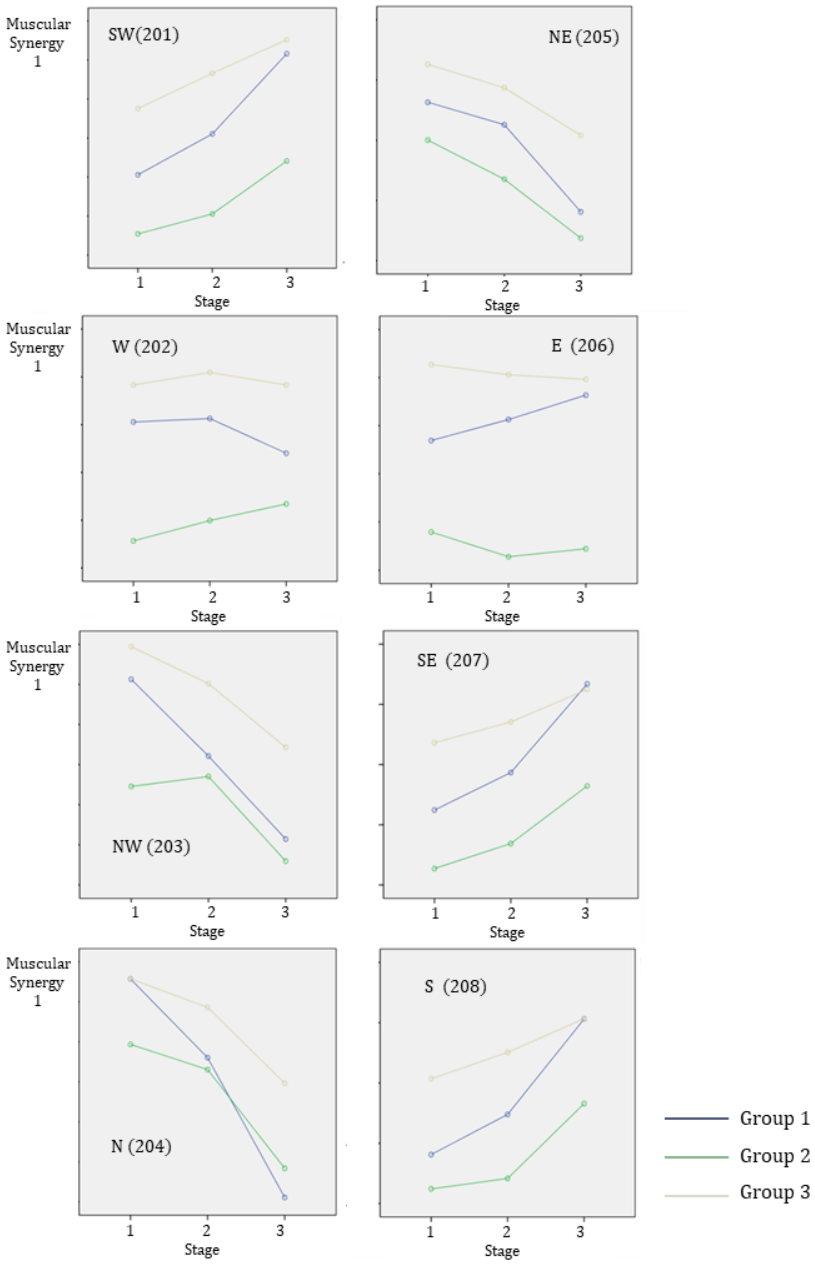


Figure 44. The muscular synergy 1 for dragging during three phases

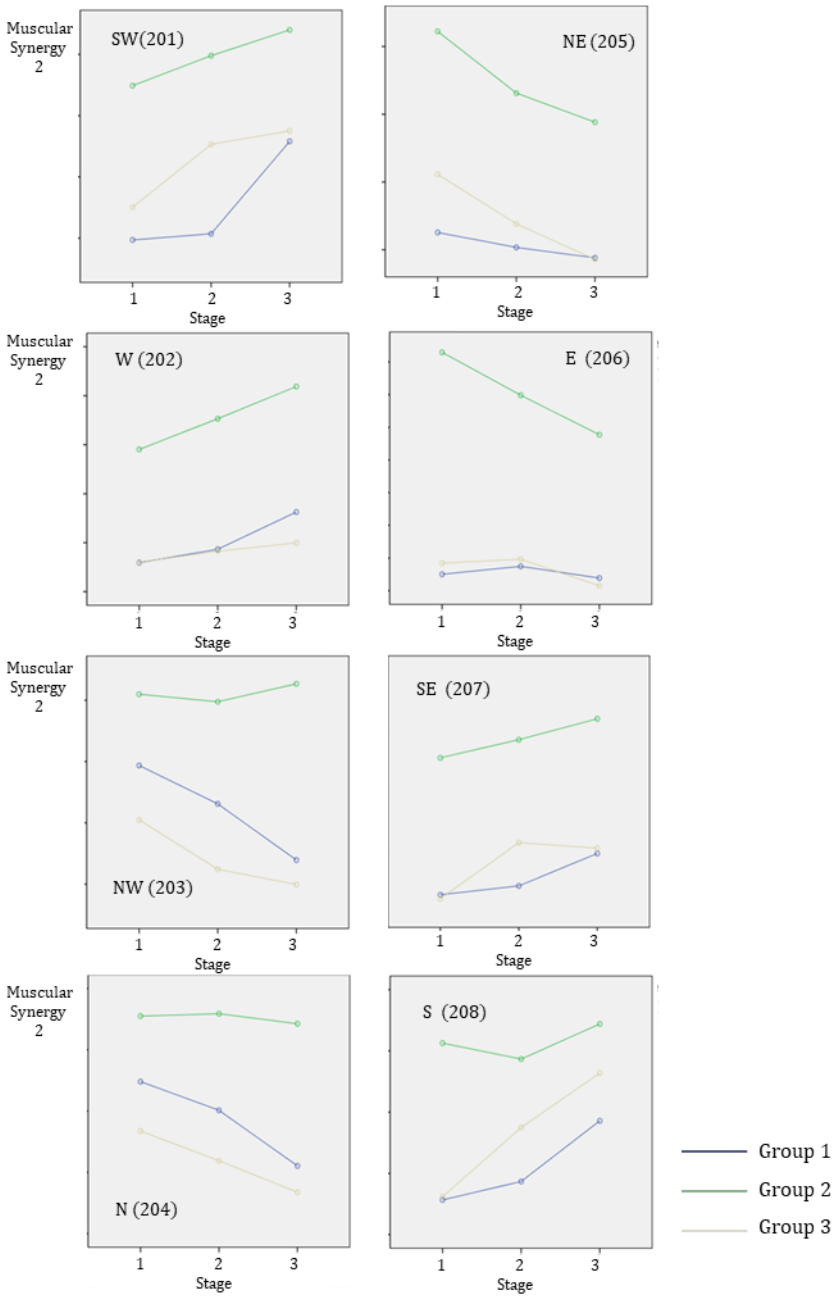


Figure 45. The muscular synergy 2 for dragging during three phases

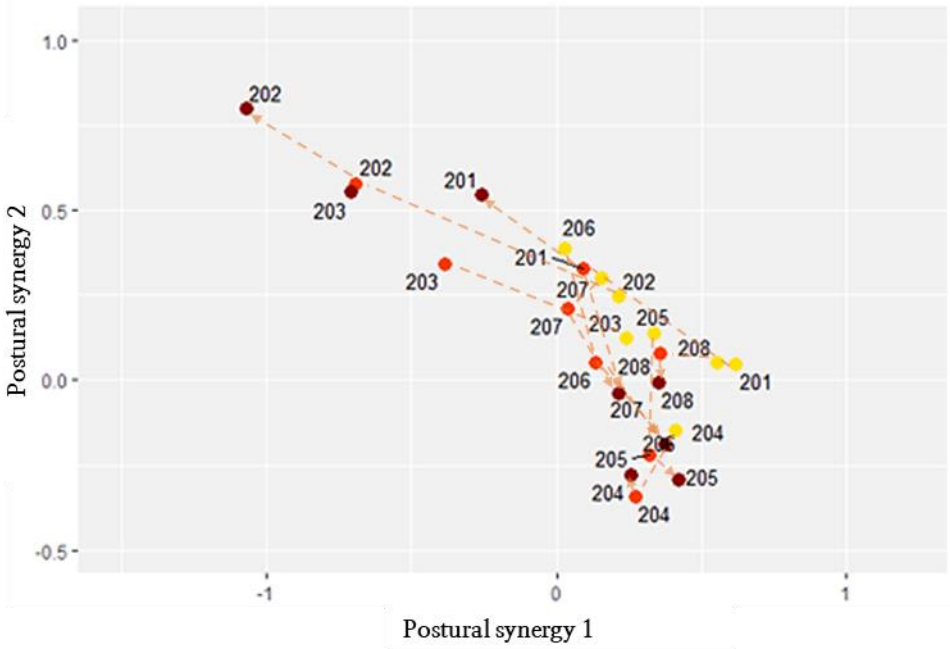


Figure 46. The 2D scatter plot of muscular synergies 1 and 2 for three drag phases

6.3 Conclusions and Discussion

This chapter aimed to determine the operational motion of a hand during use of the hand-held touchscreen device considering the effect of the hand type, task type and the task level which were the direction of dragging and the location of tapping. The synergies composing this operational motion were defined and compared according to the task type and hand type.

It is known that muscular synergies basically consist of fundamental muscle synergies which are common to people and task-specific muscle synergies to reflect the effects to reflect task property [53]. Through this experiment, it was observed that different patterns of the muscular synergies for each task and the difference between the tapping task and dragging task. The patterns of the postural synergies the tapping task were similar to the ones of the dragging tasks with little variances. In contrast with the postural synergies, the muscular synergies showed different patterns. In the tapping task, the first muscular synergy compensated the muscular synergy 2. In the dragging task, on the other hand, the first synergy was correlated to the second synergy. All hand types independently take different strategies for each direction and location for both types of synergy.

By understanding the nature of hand motion including the thumb operations, the grasp and hand tilting based on the result of this chapter, better interaction can be designed.

Chapter 7. Conclusions

7.1 Overview

The purpose of this dissertation is to analyze hand motions including grasps during operation of the handheld device with consideration of the anthropometrical characteristics of hands by defining the hand type. The materials were reviewed in the aspects of motor theory, in particular, dynamic systems theory. The synergies in dynamic systems theory describe functional dependencies among degrees of freedom by coordinating muscles or joint angles.

This dissertation was organized to flow from answering the following research questions.

Research Question 1: What is the most appropriate method to classify human hand types?

Research Question 2: Can the touchscreen device grasp posture be explained by hand grasp class of the existing taxonomy? Does a data-driven classification differ from existing grasp classification with top-down approaches?

Research Question 3: How the hand type affect hand operations when using the touchscreen devices considering with the physical properties of the device and tasks?

Research Question 4: How the result can be interpreted and applied in a practical way?

To inquire the answers for those questions, first, hands were divided into some clusters with the reduced number of hand dimensions. Then, the experiment was conducted to find whether the new grasp belongs to some of the grasps in the existing classification or not. In the experiment, grasp taxonomy was re-classified according to synergies. The grasps for the device was compared to each other by hand types defined from the previous chapter. As a result, it was revealed that the hand-held device cannot be mapped to the existing system. At the next chapter, an experiment was conducted to figure out how the hand motions were distinguished according to hand types for two tasks, tapping and dragging.

Answers for the first three the questions are:

Answer 1: Hand type give some effects on hand motions when operating handheld touchscreen devices. The effects are different according to task types and task levels.

Answer 2: The most appropriate method to classify human hand types was LPA which is model-based clustering. PCA was performed to reduce hand dimensions.

Answer 3: The grasp for hand-held touchscreen device cannot be explained by existing taxonomy for hand grasp classification. The grasp has unique characteristics in the aspects of muscular and postural

synergies. The grasp in the existing classification with top-down approach can be re-classified according to those synergies. A data-driven classification is not identical to the previous grasp classification.

The answer for the last question will be discussed in Section 7.3.

7.2 Contribution of the study

In the past decade, roboticists have successfully applied the framework of synergies to create novel design and control concepts for artificial hands, i.e., robotic hands and prostheses.

In this research, the hand motion prediction model was developed according to the result of motion analysis. Reconstructing human motion dynamics is important for understanding motor control strategies. Main expected effects of this research are as follows.

- A better understanding of human behaviors when using handheld touchscreen devices. This dissertation suggests hand motions for hand-held touchscreen device not by observational measure, but the measure which can explain the motions through more fundamental approach.
- Designing better interactions for a smartphone or other kinds of a small touchscreen device. Screen area is not identical over the area in terms of operating posture and required muscle activities. This is more than dividing the area.
- Appling Synergies defined in this dissertation to design robot hand or prosthetic hand. This will be useful to explain redundancy of degree of freedom.

7.3 Design application

The results of this study can suggest design guidelines to the designers who create applications or user interfaces of smartphones. UI components need to be tapped should not be placed at the position that makes fingers be bent more or muscle activities higher. From this aspect, points which limit thumb movement such as 101, 104, 113 and 115 are not recommended (see Figure 47, Figure 48). Fingers were bent as much as the case of grasping dumbbell or battery to tap those points. Contrastively the best locations when considering postural and muscular comfort are 106, 108, 113 and 110.

Major smartphone operating systems including iOS and Android place the back or the hierarchical up button at the point 101 mainly, however, this is not a good way from the finger comfort perspective for the users who operate the device in a single hand. Although Apple's human interface guideline recommend giving gesture interaction for historical back or hierarchical up function, it is not enough because that area is also used as function button such as 'edit' or 'more option' button.

To resolve this kind of problems, iOS and Android are moving tap button from top to bottom. However as mentioned in the above paragraph, the lower area is not the golden key. Extremely left or right area such as 113 or 115 are also hard to tap using the thumb. This result agreed with a previous study which concluded that greater effort was perceived for the thumb when using the keypad in the right bottom corner of mobile phone [27].

Also, many buttons such as tap switch or symbol key in the keyboard are placed at those areas, and this is a clear mistake that lower area is always thought to be easy-to-tap. For better improvements, gesture interaction using dragging might be an appropriate way.

Especially, for muscular comfort, the point 113 and 110 are the worst position to place touch components. As shown in Figure 48, muscle activities when tapping that area are way much higher than any grasping behaviors. This tells that extremely left area is the worst one to put touchable elements for right-handed users.

For dragging task, thumb flexed more when dragging to the west side such as 201, 202, and 203. From thumb muscle comfort perspective, dragging to the east side is much easier to do to a left side. Dragging to N, S or E were relatively easier than the left side, NE, or SE (Figure 48).

This result gives us several design insights to improve smartphone gesture interactions. Because dragging to N is easier than to the left side, swiping up interaction is much better than swiping left one. There are two ways to give a series of card-type pages to users: one is a vertical scroll and the other is a horizontal scroll. Based on the results, the vertical scroll is more appropriate than horizontal scroll in the one-hand operation of a touchscreen device.

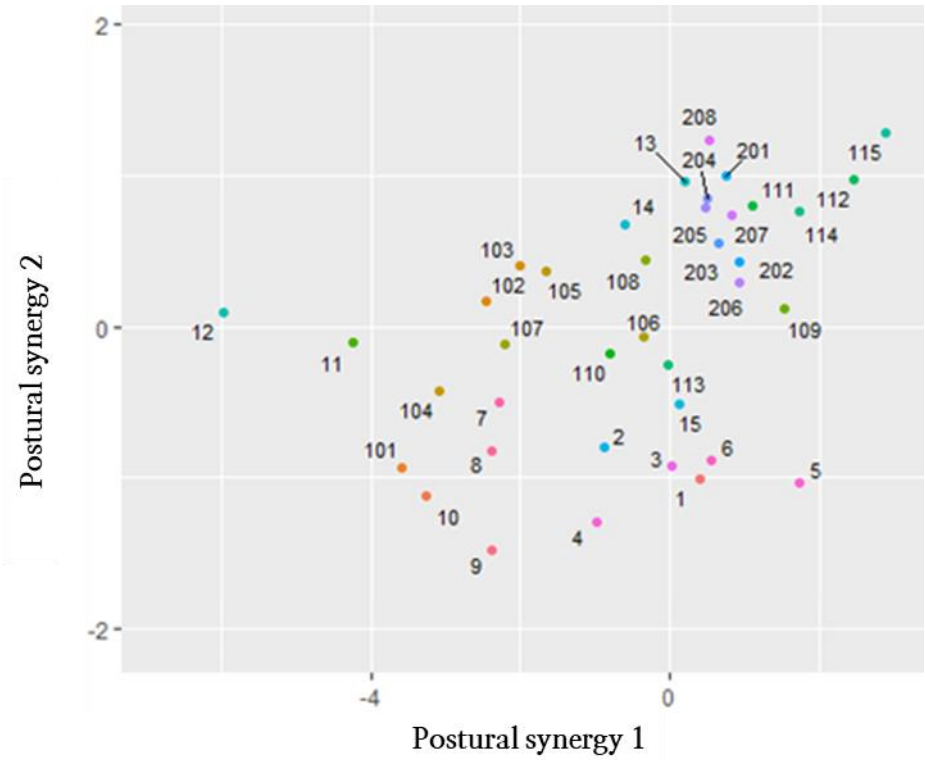


Figure 47. The result of hand postures explained by postural synergy 1 and 2 for the grasps of objects and during tapping and dragging tasks.

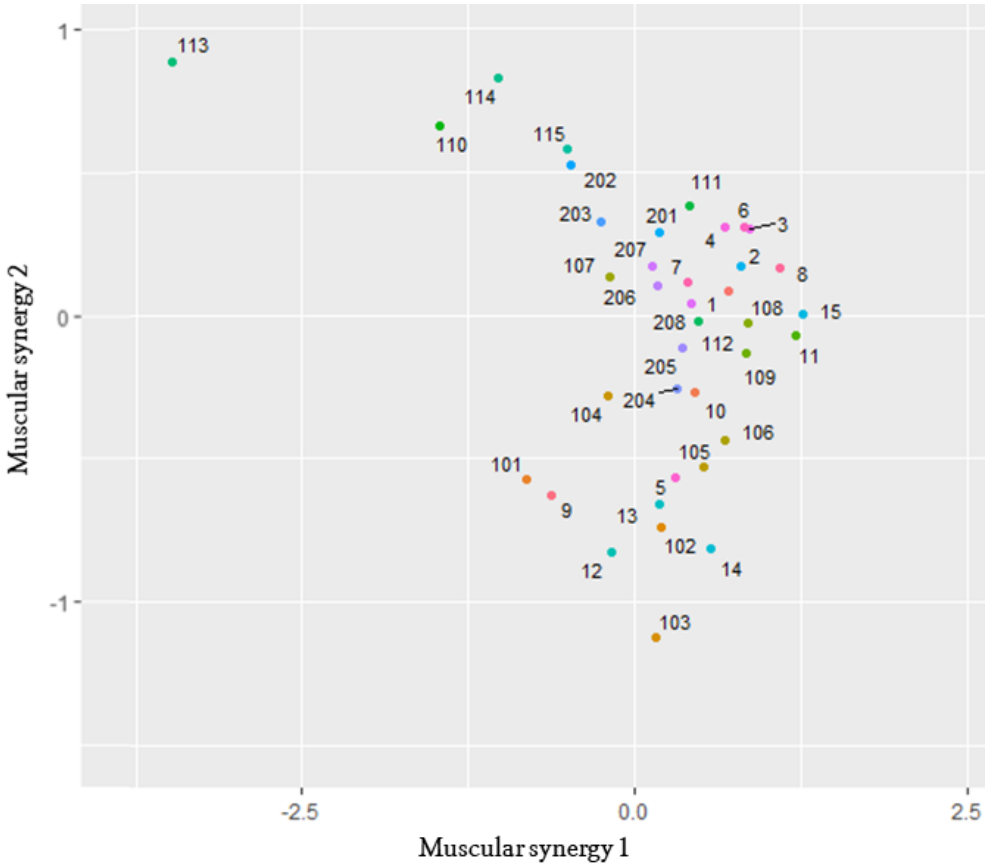


Figure 48. The result of hand postures explained by muscular synergy 1 and 2 for the grasps of objects and during tapping and dragging tasks.

7.4 Limitations and further study

This dissertation has some limitations. For example, the experiments conducted focused on a young generation whose ages were the 20s or 30s. According to several studies, age affects motor control ability, so as for hand motions. For further study, if possible, the age variation can be broader than this dissertation to verify the effect of age.

Moreover, the sensors for measuring joint angles only covered ten joints except for distal interphalangeal joints (DIP) although the angle of DIPs can be roughly expected by those of PIPs. Wrist angles were not in the scope of this dissertation. Wrist abduction/adduction, as well as flexion/extension, are other important factors to inquire hand motions. Contact area or contact pressure is another variable which implies valuable information during manual operations.

Mathematical modeling using hand dimensions and form factors to predict hand motion using dynamic systems equation is another missing topic in this dissertation. In the future study, the author will make an effort to model thumb operations and grasp.

Lastly, for later application, the subjective rate for task levels for each task may be helpful if it is connected to the findings of this dissertation. The experiment did not include user satisfaction, but without this information, the result may not be easily applied to practice.

References

1. Bao, S. and B. Silverstein, *Estimation of hand force in ergonomic job evaluations.* Ergonomics, 2005. **48**(3): p. 288-301.
2. Schwarz, R.J., *The anatomy and mechanics of the human hand.* Artificial limbs, 1955. **22**.
3. Jee, S.-c. and M.H. Yun, *An anthropometric survey of Korean hand and hand shape types.* International Journal of Industrial Ergonomics, 2016. **53**: p. 10-18.
4. Davies, B., et al., *A comparison of hand anthropometry of females in three ethnic groups.* Ergonomics, 1980. **23**(2): p. 179-182.
5. Mandahawi, N., et al., *Hand anthropometry survey for the Jordanian population.* International Journal of Industrial Ergonomics, 2008. **38**(11): p. 966-976.
6. Yun, M.H., *A hand posture measurement system for the analysis of manual tool handling tasks.* 1994, Pennsylvania State University.
7. Blackwell, J.R., K.W. Kornatz, and E.M. Heath, *Effect of grip span on maximal grip force and fatigue of flexor digitorum superficialis.* Applied ergonomics, 1999. **30**(5): p. 401-405.
8. McGorry, R.W., *A system for the measurement of grip forces and applied moments during hand tool use.* Applied ergonomics, 2001. **32**(3): p. 271-279.
9. Rosén, B. and G. Lundborg, *Training with a mirror in rehabilitation of the hand.* Scandinavian journal of plastic and reconstructive surgery and hand surgery, 2005. **39**(2): p. 104-108.
10. Lambercy, O., et al., *A haptic knob for rehabilitation of hand function.* IEEE Transactions on Neural Systems and Rehabilitation Engineering, 2007. **15**(3): p. 356-366.
11. Sanders, R.H., *Hydrodynamic characteristics of a swimmer's hand.* Journal of applied biomechanics, 1999. **15**(1): p. 3-26.
12. Barris, S. and C. Button, *A review of vision-based motion analysis in sport.* Sports Medicine, 2008. **38**(12): p. 1025-1043.

13. Phillips, J.G., R.P. Ogeil, and C. Best, *Motor constancy and the upsizing of handwriting.* Human movement science, 2009. **28**(5): p. 578-587.
14. Farahani, S.D., et al., *Prediction of closed-chain human arm dynamics in a crank-rotation task.* Journal of biomechanics, 2016. **49**(13): p. 2684-2693.
15. Kaminski, T. and A. Gentile, *Joint control strategies and hand trajectories in multijoint pointing movements.* Journal of Motor Behavior, 1986. **18**(3): p. 261-278.
16. Chang, S., S. Park, and A. Freivalds, *Ergonomic evaluation of the effects of handle types on garden tools.* International journal of industrial ergonomics, 1999. **24**(1): p. 99-105.
17. Shim, J.-m., *The Effect of Carpal Tunnel Changes on Smartphone Users.* Journal of Physical Therapy Science, 2012. **24**(12): p. 1251-1253.
18. Ko, P.-H., Y.-H. Hwang, and H.-W. Liang, *Influence of smartphone use styles on typing performance and biomechanical exposure.* Ergonomics, 2016. **59**(6): p. 821-828.
19. İNal, E.E., et al., *Effects of smartphone overuse on hand function, pinch strength, and the median nerve.* Muscle & nerve, 2015. **52**(2): p. 183-188.
20. Wolniewicz, C.A., et al., *Problematic smartphone use and relations with negative affect, fear of missing out, and fear of negative and positive evaluation.* Psychiatry research, 2018. **262**: p. 618-623.
21. Wikipedia.org. *List of countries by smartphone penetration*. 2018 [cited 2018 Dec. 01]; Available from: https://en.wikipedia.org/wiki/List_of_countries_by_smartphone_penetration
22. Trudeau, M.B., et al. *Thumb Motor Performance is Greater for Two-Handed Grip Compared to Single-Handed Grip on a Mobile Phone*. in *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*. 2012. SAGE Publications.
23. Lee, S., et al., *Determining Ergonomic Smartphone Forms With High Grip Comfort and Attractive Design.* Human factors, 2018: p. 0018720818792758.
24. Xiong, J. and S. Muraki, *Effects of age, thumb length and screen size on thumb movement coverage on smartphone touchscreens.* International

Journal of Industrial Ergonomics, 2016. **53**: p. 140-148.

25. Xiong, J. and S. Muraki, *An ergonomics study of thumb movements on smartphone touch screen.* Ergonomics, 2014. **57**(6): p. 943-955.
26. Jonsson, P., et al., *Thumb joint movement and muscular activity during mobile phone texting – A methodological study.* Journal of Electromyography and Kinesiology, 2011. **21**(2): p. 363-370.
27. Hogg, N.A., *Design of thumb keyboards: Performance, effort and kinematics.* 2010, University of Waterloo.
28. Erkol İnal, E., et al., *Effects of smartphone overuse on hand function, pinch strength, and the median nerve.* Muscle & nerve, 2015.
29. Henze, N., E. Rukzio, and S. Boll. *100,000,000 taps: analysis and improvement of touch performance in the large.* in *Proceedings of the 13th International Conference on Human Computer Interaction with Mobile Devices and Services*. 2011. ACM.
30. Xie, Y., et al., *A comparison of muscle activity in using touchscreen smartphone among young people with and without chronic neck – shoulder pain.* Ergonomics, 2016. **59**(1): p. 61-72.
31. Endo, H., *Application of robotic manipulability indices to evaluate thumb performance during smartphone touch operations.* Ergonomics, 2015. **58**(5): p. 736-747.
32. Gold, J., et al., *Postures, typing strategies, and gender differences in mobile device usage: An observational study.* Applied Ergonomics, 2012. **43**(2): p. 408-412.
33. Wang, E.M.-y. and S.S.-y. Shih. *A study on thumb and index finger operated interface for personal mobile devices: Mobile phone keypad and joystick.* in *Industrial Engineering and Engineering Management, 2009. IE&EM'09. 16th International Conference on*. 2009. IEEE.
34. Choi, C.-M., et al., *EMG-based Real-time Finger Force Estimation for Human-Machine Interaction.* Journal of the Korean Society for Precision Engineering, 2009. **26**(8): p. 132-141.
35. Freivalds, A., *Biomechanics of the upper limbs: mechanics, modeling and*

musculoskeletal injuries. 2011: CRC press.

36. Jacobson, M., et al. *Comparison of surface to indwelling extrinsic finger muscle EMG during use of computer pointing devices*. in *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*. 1998. SAGE Publications Sage CA: Los Angeles, CA.
37. Emerson, E.T., T.J. Krizek, and D.P. Greenwald, *Anatomy, physiology, and functional restoration of the thumb.* Annals of plastic surgery, 1996. **36**(2): p. 180-191.
38. Tang, J., X. Zhang, and Z.-M.J.E. Li, *Operational and maximal workspace of the thumb.* 2008. **51**(7): p. 1109-1118.
39. Chao, E.Y., *Biomechanics of the hand: a basic research study*. 1989: World Scientific.
40. Magill, R.A. and D.I. Anderson, *Motor learning and control: Concepts and applications*. Vol. 11. 2007: McGraw-Hill New York.
41. Thelen, E., *The (re) discovery of motor development: Learning new things from an old field.* Developmental Psychology, 1989. **25**(6): p. 946.
42. Haywood, K. and N. Getchell, *Life Span Motor Development 6th Edition*. 2014: Human Kinetics.
43. Latash, M.L., et al., *Motor control theories and their applications.* Medicina (Kaunas, Lithuania), 2010. **46**(6): p. 382.
44. Ranganathan, R. and K.M. Newell, *Online feedback and the regulation of degrees of freedom in motor control.* Human movement science, 2008. **27**(4): p. 577-589.
45. Tagliabue, M., et al., *Differences between kinematic synergies and muscle synergies during two-digit grasping.* Frontiers in human neuroscience, 2015. **9**: p. 165.
46. Santello, M., M. Flanders, and J.F. Soechting, *Postural hand synergies for tool use.* Journal of Neuroscience, 1998. **18**(23): p. 10105-10115.
47. Mason, C.R., J.E. Gomez, and T.J.J.J.o.N. Ebner, *Hand synergies during reach-to-grasp.* 2001. **86**(6): p. 2896-2910.
48. Santello, M., et al., *Hand synergies: integration of robotics and neuroscience*

for understanding the control of biological and artificial hands. Physics of life reviews, 2016. **17**: p. 1-23.

49. Todorov, E. and Z. Ghahramani. *Analysis of the synergies underlying complex hand manipulation.* in *Engineering in Medicine and Biology Society, 2004. IEMBS'04. 26th Annual International Conference of the IEEE.* 2004. IEEE.
50. De Luca, C.J., *The use of surface electromyography in biomechanics.* Journal of applied biomechanics, 1997. **13**(2): p. 135-163.
51. Castellini, C. and P. van der Smagt, *Evidence of muscle synergies during human grasping.* Biological cybernetics, 2013. **107**(2): p. 233-245.
52. Weiss, E.J. and M. Flanders, *Muscular and postural synergies of the human hand.* Journal of neurophysiology, 2004. **92**(1): p. 523-535.
53. Thakur, P.H., A.J. Bastian, and S.S.J.J.o.N. Hsiao, *Multidigit movement synergies of the human hand in an unconstrained haptic exploration task.* 2008. **28**(6): p. 1271-1281.
54. Ajiboye, A.B. and R.J.J.o.n.e. Weir, *Muscle synergies as a predictive framework for the EMG patterns of new hand postures.* 2009. **6**(3): p. 036004.
55. Committee, H., *Guidelines for using anthropometric data in product design.* 2004: Human Factors and Ergonomics Society.
56. Garneau, C.J. and M.B. Parkinson, *Including preference in anthropometry-driven models for design.* Journal of Mechanical Design, 2009. **131**(10): p. 101006.
57. Pheasant, S.T. and C.M. Haslegrave, *Bodyspace: anthropometry, ergonomics, and the design of work.* 2006: CRC Press.
58. KROEMER, K.H., *Engineering anthropometry.* Ergonomics, 1989. **32**(7): p. 767-784.
59. Herron, R., *Anthropometry: Definition, Uses and Methods of Measurement.* International Encyclopedia of Ergonomics and Human Factors-3 Volume Set, 2000: p. 879.
60. Robinette, K.M., H. Daanen, and E. Paquet. *The CAESAR project: a 3-D surface anthropometry survey.* in *3-D Digital Imaging and Modeling, 1999. Proceedings. Second International Conference on.* 1999. IEEE.

61. Kim, J.Y., J.W. You, and M.S. Kim, *South Korean anthropometric data and survey methodology: 'Size Korea' project.* Ergonomics, 2017. 60(11): p. 1586-1596.
62. Roebuck, J.A., K.H. Kroemer, and W.G. Thomson, *Engineering anthropometry methods*. Vol. 3. 1975: John Wiley & Sons.
63. Yu, H.-C., S.-U. Sin, and T.-B. Ryu, *A Classification Method of Anthropometric Variables for Improved Usability of Anthropometric Data.* Journal of the Ergonomics Society of Korea, 2004. 23(3): p. 13-24.
64. Kroemer, K.H., H.J. Kroemer, and K.E. Kroemer-Elbert, *Engineering physiology: bases of human factors engineering/ergonomics*. 2010: Springer Science & Business Media.
65. Salvendy, G., *Hand size and assembly performance.* AIIE Transactions, 1971. 3(1): p. 32-36.
66. Buchholz, B., T.J. Armstrong, and S.A. Goldstein, *Anthropometric data for describing the kinematics of the human hand.* Ergonomics, 1992. 35(3): p. 261-273.
67. Garrett, J.W., *The adult human hand: some anthropometric and biomechanical considerations.* Human factors, 1971. 13(2): p. 117-131.
68. Armstrong, T. and D. Chaffin, *Carpal tunnel syndrome and selected personal attributes.* Journal of occupational medicine.: official publication of the Industrial Medical Association, 1979. 21(7): p. 481-486.
69. Kong, Y.-K., et al., *Evaluation of handle design characteristics in a maximum screwdriving torque task.* 2007. 50(9): p. 1404-1418.
70. Kwon, O., et al., *Determination and application of key dimensions for a sizing system of glove by analyzing the relationships between hand anthropometric variables.* Journal of the Ergonomics Society of Korea, 2004. 23(3): p. 25-38.
71. Chang, J., et al. *Determination of bicycle handle diameters considering hand anthropometric data and user satisfaction*. in *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*. 2010. SAGE Publications Sage CA: Los Angeles, CA.
72. Cakit, E., et al., *A survey of hand anthropometry and biomechanical*

measurements of dentistry students in Turkey. Human Factors and Ergonomics in Manufacturing & Service Industries, 2014. **24**(6): p. 739-753.

73. Majumder, J. and L.K. Sharma, *Identifying Body Size Group Clusters from Anthropometric Body Composition Indicators.* Journal of Ecophysiology and Occupational Health, 2015. **15**(3/4): p. 81.
74. Olds, T., et al., *Somatotyping using 3D anthropometry: a cluster analysis.* Journal of sports sciences, 2013. **31**(9): p. 936-944.
75. Cottle, F.S., *Statistical human body form classification: Methodology development and application.* 2012: Auburn University.
76. Pheasant, S. and J. Scriven. *Sex differences in strength: Some implications for the design of handtools.* in *Proceedings of the Ergonomics Society's Annual Conference*. 1983.
77. Härkönen, R., M. Piirtomaa, and H. Alaranta, *Grip strength and hand position of the dynamometer in 204 Finnish adults.* Journal of Hand Surgery, 1993. **18**(1): p. 129-132.
78. Eksioglu, M., *Relative optimum grip span as a function of hand anthropometry.* International Journal of Industrial Ergonomics, 2004. **34**(1): p. 1-12.
79. Oh, S. and R.G. Radwin, *Pistol grip power tool handle and trigger size effects on grip exertions and operator preference.* Human Factors, 1993. **35**(3): p. 551-569.
80. Kim, S.-H. and D.-H. Kee, *Classification and identification of Korean hand shapes based on anthropometric hand data analysis.* Journal of the Korea Safety Management and Science, 2012. **14**(1): p. 75-85.
81. Jung, M.-C., D.-M. Kim, and Y.-K. Kong, *Evaluation of individual finger force to grip strength in various grip spans and hand sizes.* Journal of the Ergonomics Society of Korea, 2007. **26**(3): p. 59-65.
82. MacKenzie, C.L. and T. Iberall, *The grasping hand.* Vol. 104. 1994: Elsevier.
83. Cutkosky, M.R., *On grasp choice, grasp models, and the design of hands for manufacturing tasks.* IEEE Transactions on robotics and automation, 1989. **5**(3): p. 269-279.

84. Napier, J.R., *The prehensile movements of the human hand.* The Journal of bone and joint surgery. British volume, 1956. **38**(4): p. 902-913.
85. Elliott, J.M. and K. Connolly, *A classification of manipulative hand movements.* Developmental Medicine & Child Neurology, 1984. **26**(3): p. 283-296.
86. Kamakura, N., et al., *Patterns of static prehension in normal hands.* American Journal of Occupational Therapy, 1980. **34**(7): p. 437-445.
87. Zheng, J.Z., S. De La Rosa, and A.M. Dollar. *An investigation of grasp type and frequency in daily household and machine shop tasks*. in *Robotics and Automation (ICRA), 2011 IEEE International Conference on*. 2011. IEEE.
88. Liu, J., et al. *A taxonomy of everyday grasps in action*. in *Humanoid Robots (Humanoids), 2014 14th IEEE-RAS International Conference on*. 2014. IEEE.
89. Feix, T., et al. *A comprehensive grasp taxonomy*. in *Robotics, science and systems: workshop on understanding the human hand for advancing robotic manipulation*. 2009.
90. Kim, K.-E., et al. *Hand grip pattern recognition for mobile user interfaces*. in *Proceedings of the National Conference on Artificial Intelligence*. 2006. Menlo Park, CA; Cambridge, MA; London; AAAI Press; MIT Press; 1999.
91. Merletti, R., P.A. Parker, and P.J. Parker, *Electromyography: physiology, engineering, and non-invasive applications*. Vol. 11. 2004: John Wiley & Sons.
92. Arkenbout, E.A., J.C. de Winter, and P. Breedveld, *Robust hand motion tracking through data fusion of 5DT data glove and nimble VR Kinect camera measurements.* Sensors, 2015. **15**(12): p. 31644-31671.
93. Luzanin, O. and M. Plancak, *Hand gesture recognition using low-budget data glove and cluster-trained probabilistic neural network.* Assembly Automation, 2014. **34**(1): p. 94-105.
94. Veerapalli, L. *Sign language recognition through fusion of 5DT data glove and camera based information*. in *Advance Computing Conference (IACC), 2015 IEEE International*. 2015. IEEE.
95. Shukor, A.Z., et al., *A new data glove approach for Malaysian sign language detection.* Procedia Computer Science, 2015. **76**: p. 60-67.

96. Bundhoo, V. and E.J. Park. *Design of an artificial muscle actuated finger towards biomimetic prosthetic hands.* in *Advanced Robotics, 2005. ICAR'05. Proceedings., 12th International Conference on*. 2005. IEEE.

97. Griffin, W.B., et al. *Calibration and mapping of a human hand for dexterous telemanipulation.* in *ASME IMECE 2000 Symposium on Haptic Interfaces for Virtual Environments and Teleoperator Systems*. 2000.

98. Zollo, L., et al., *Biomechatronic design and control of an anthropomorphic artificial hand for prosthetic and robotic applications.* IEEE/ASME Transactions On Mechatronics, 2007. **12**(4): p. 418-429.

99. Page, T., *Usability of text input interfaces in smartphones.* Journal of Design Research, 2013. **11**(1): p. 39-56.

100. Lee, S., et al., *Determining Ergonomic Smartphone Forms With High Grip Comfort and Attractive Design.* Human factors, 2019. **61**(1): p. 90-104.

101. Loebig, T., et al., *Radial Instability of the Metacarpophalangeal Joint of the Thumb: A biomechanical investigation.* Journal of Hand Surgery, 1995. **20**(1): p. 102-104.

102. Walsh, T., E. Delahunt, and U.M. Persson, *Effects of taping on thumb alignment and force application during PA mobilisations.* Manual therapy, 2011. **16**(3): p. 264-269.

103. Janghyun Cho, *Modeling touch gestures to propose optimal design guidelines based on human performance measures*. 2017, Seoul National university.

104. Quinn, P. and S. Zhai, *Modeling gesture-typing movements.* Human-Computer Interaction, 2016: p. 1-47.

105. Engelbrecht, S.E., *Minimum principles in motor control.* Journal of Mathematical Psychology, 2001. **45**(3): p. 497-542.

106. Ahn, S.H., et al., *Effects of Grip Curvature and Hand Anthropometry for the Unimanual Operation of Touchscreen Handheld Devices.* Human Factors and Ergonomics in Manufacturing & Service Industries, 2016. **26**(3): p. 367-380.

107. Le, H.V., et al. *Fingers' Range and Comfortable Area for One-Handed Smartphone Interaction Beyond the Touchscreen*. in *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems*. 2018. ACM.

108. Yoo, H., J. Yoon, and H. Ji. *Index finger zone: Study on touchable area expandability using thumb and index finger*. in *Proceedings of the 17th International Conference on Human-Computer Interaction with Mobile Devices and Services Adjunct*. 2015. ACM.
109. Gustafsson, E., et al., *Technique, muscle activity and kinematic differences in young adults texting on mobile phones.* Ergonomics, 2011. **54**(5): p. 477-487.
110. Nass., et al. *Improving automotive safety by pairing driver emotion and car voice emotion*. 2005. ACM.
111. Jain, A.K., R.P.W. Duin, and J. Mao, *Statistical pattern recognition: A review.* IEEE Transactions on pattern analysis and machine intelligence, 2000. **22**(1): p. 4-37.
112. Xu, R. and D. Wunsch, *Clustering*. Vol. 10. 2008: John Wiley & Sons.
113. Dunteman, G.H., *Principal component analysis. Quantitative applications in the social sciences series (vol. 69)*. 1989, Thousand Oaks, CA: Sage Publications.
114. Dunteman, G.H., *Principal components analysis*. 1989: Sage.
115. Niu, J., et al. *A comparative study on application of data mining technique in human shape clustering: Principal component analysis vs. factor analysis*. in *Industrial Electronics and Applications (ICIEA), 2010 the 5th IEEE Conference on*. 2010. IEEE.
116. Bexek, J., *Pattern recognition with fuzzy objective function algorithm*. 1981, Plenum Press.
117. Dunn, J.C., *A fuzzy relative of the ISODATA process and its use in detecting compact well-separated clusters.* 1973.
118. Suganya, R., R.J.I.J.o.S. Shanthi, and R. Publications, *Fuzzy c-means algorithm-a review.* 2012. **2**(11): p. 1.
119. Ali, A.M., G.C. Karmakar, and L.S.J.J.o.A.C. Dooley, *Review on fuzzy clustering algorithms.* 2008. **2**(3): p. 169-181.
120. Di Martino, F., V. Loia, and S.J.I.J.o.H.I.S. Sessa, *Extended fuzzy C-means clustering algorithm for hotspot events in spatial analysis.* 2008. **5**(1): p. 31-44.

121. Di Martino, F. and S.J.J.o.U.S. Sessa, *Implementation of the extended fuzzy C-means algorithm in geographic information systems.* 2009. 3(4): p. 298-306.

122. Jipkate, B.R. and V.J.I.J.O.C.E.R. Gohokar, *A comparative analysis of fuzzy c-means clustering and k means clustering algorithms.* 2012. 2(3): p. 737-739.

123. Panda, S., et al., *Comparing fuzzy-C means and K-means clustering techniques: a comprehensive study*, in *Advances in Computer Science, Engineering & Applications*. 2012, Springer. p. 451-460.

124. Ghosh, S., S.K.J.I.J.o.A.C.S. Dubey, and Applications, *Comparative analysis of k-means and fuzzy c-means algorithms.* 2013. 4(4).

125. Bora, D.J., D. Gupta, and A.J.a.p.a. Kumar, *A comparative study between fuzzy clustering algorithm and hard clustering algorithm.* 2014.

126. Kovács, F., C. Legány, and A. Babos. *Cluster validity measurement techniques.* in *6th International symposium of hungarian researchers on computational intelligence*. 2005. Citeseer.

127. Ketchen, D.J. and C.L. Shook, *The application of cluster analysis in strategic management research: an analysis and critique.* Strategic management journal, 1996. 17(6): p. 441-458.

128. Pastor, D.A., et al., *A latent profile analysis of college students' achievement goal orientation.* Contemporary Educational Psychology, 2007. 32(1): p. 8-47.

129. Pereira, A., et al., *Holding a tablet computer with one hand: effect of tablet design features on biomechanics and subjective usability among users with small hands.* Ergonomics, 2013. 56(9): p. 1363-1375.

130. Kim, K., et al., *A comparative evaluation about force and fatigue on thumb according to input type for repetitive use of mobile phone.* Journal of Biomedical Engineering Research, 2011. 32(4): p. 312-318.

131. Kietrys, D.M., et al., *Mobile input device type, texting style and screen size influence upper extremity and trapezius muscle activity, and cervical posture while texting.* Applied ergonomics, 2015. 50: p. 98-104.

132. Kwon, S., et al., *A study on the relationships among hand muscles and form factors of large-screen curved mobile devices.* International Journal of Industrial Ergonomics, 2016. **56**: p. 17-24.
133. Buchner, H.J., M.J. Hines, and H. Hemami, *A dynamic model for finger interphalangeal coordination.* Journal of Biomechanics, 1988. **21**(6): p. 459-468.
134. Schieber, M.H. and M. Santello, *Hand function: peripheral and central constraints on performance.* Journal of Applied Physiology, 2004. **96**(6): p. 2293-2300.
135. Cram, J.R., *Cram's introduction to surface electromyography*. 2011: Jones & Bartlett Learning.
136. d'Avella, A., P. Saltiel, and E. Bizzi, *Combinations of muscle synergies in the construction of a natural motor behavior.* Nature neuroscience, 2003. **6**(3): p. 300.
137. Feix, T., et al., *The grasp taxonomy of human grasp types.* IEEE Transactions on Human-Machine Systems, 2016. **46**(1): p. 66-77.
138. Sheskin, D.J., *Handbook of parametric and nonparametric statistical procedures*. 2003: crc Press.
139. Seo, N.J. and T.J. Armstrong, *Investigation of grip force, normal force, contact area, hand size, and handle size for cylindrical handles.* Human Factors, 2008. **50**(5): p. 734-744.
140. Pelosi, M., et al., *A grip study for talk and data modes in mobile phones.* 2009. **57**(4): p. 856-865.
141. Hermens, H.J., et al., *Development of recommendations for SEMG sensors and sensor placement procedures.* Journal of electromyography and Kinesiology, 2000. **10**(5): p. 361-374.

Appendix

Grasp classifications developed in anthropology, medicine, biomechanics, robotics, and occupational therapy [82]

Researchers	Grasp types	
Cooney and Chao (1977)	grasp	tip pinch
	palmar pinch	lateral pinch
Cutkosky (1989)	large diameter heavy wrap	4 finger precision grasp
	small diameter heavy wrap	3 finger precision grasp
	medium wrap	2 finger precision grasp
	adducted thumb wrap	disk precision grasp
	light tool wrap	spherical precision grasp
	disk power grasp	tripod precision grasp
	spherical power grasp	lateral pinch
	5 finger precision grasp	hook, platform, push
Elliott and Connolly (1984)	palmar grip	rock
	dynamic tripod	radial roll
	pinch	index roll
	squeeze	full roll
	twiddle	interdigital step
	rotary step	palmar slide
	linear step	
Griffiths (1943)	cylinder grip	ball grip
Iberall et al. (1986)	palm opposition	side opposition
	pad opposition	

Jacobson and Sperling (1976)	coding system for fingers, finger positions, finger joint positions, contact surfaces, and orientation of object's longitudinal axis with respect to the hand	
Kamakura et al. (1980)	power grip-standard	parallel extension grip
	power grip-index extension	tripod grip
	power grip-distal	tripod grip-var. 1
	power grip-extension	tripod grip-var. 2
	parallel mild flexion grip	lateral grip
	tip prehension	power grip-hook
	surrounding mild flexion grip	adduction grip
Kapandji (1982)	cylindrical palmar	tetradigital-pulp & side
	spherical palmar	tetradigital pulp to side
	digito-palmar	tetradigital by pulp
	subterminal pollici-digital	pentadigital-pulp&side
	terminal pollici-digital	panoramic pentadigital
	subtermino-lateral pollici-digital	pentadigital cleft
	interdigital latero-lateral	directional grip
	tridigital grips	gravity-dependent grips
		dynamic grips
Kroemer (1986)	disk grip	lateral grip
	collect enclosure	precision or writing grip
	power grasp	hook grip
	pinch or pliers grip	finger touch
	tip grip	palm touch
Landsmeer (1942)	power grasp	precision handling
Lyons (1985)	encompass grasp	lateral grasp
	precision grasp	

Lister (1977)	span power grasp precision pinch pulp pinch	chuck grip key pinch hook grip flat hand
Liu and Bekey (1986)	power grasp cylindrical grip span precision pinch	pulp pinch chuck grip lateral pinch hook grip
McBride (1942)	whole hand grasping palm, digits grasping	thumb, finger grasping
Napier (1956)	power grip precision grip	combined grip hook grip
Patkin (1981)	power grip external precision grip internal precision grip	pinch grip double grip (ulnar storage)
Schlesinger (1919)	open fisted cylindrical grasp close fisted cylindrical grasp spherical prehension palmar prehension (pincer) tip prehension lateral prehension hook prehension	cylindrical w/ add. thumb flat/thin (2 finger) pincer large (5 fingered) pincer three-jaw chuck nippers prehension
Skerik et al. (1971)	power grip two point palmar pinch three point palmar pinch	tip pinch link grip (lateral pinch) hook grip
Slocum and Pratt (1946)	grasp pinch	hook

Sollerman (1980)	diagonal volar grip transverse volar grip spherical volar grip pulp pinch	tripod pinch five-fingered pinch lateral pinch extension grip
Taylor (1948)	palmar prehension (3 jaw chunk) tip prehension	lateral prehension

국문 초록

손은 인간이 가지고 있는 모든 기관 중 가장 세밀한 기능을 할 수 있는 기관이며, 따라서 가장 효과적으로 기기 및 각종 도구를 사용할 수 있는 기능을 한다. 현시대에 가장 많이 사용되는 기기로 당연 스마트폰을 꼽을 수 있다. 스마트폰과 관련된 기존 연구는 각종 근육 및 손가락 각도를 측정한 자료를 바탕으로 엄지의 조작 능력이나 엄지의 동작 범위 등에 초점을 맞추었다. 그러나 기존 연구는 이러한 주제에만 제한되어 있어, 도구 사용에 기본인 그립에 관해서는 크게 다루지 않았다. 또한, 기존 연구는 대부분 손가락의 각도 및 개별적인 근육 사용량을 측정한 결과를 바탕으로 이루어져 인간이 어떻게 여러 근육이나 손가락을 동시에 제어하는지에 대해 설명 할 수 있는 동작 제어(motor control) 관점에서 분석하지 못하였다.

동작 제어 이론 중 가장 유력한 이론 중 하나인 dynamic systems 이론은 인간의 동작을 사람, 과업 및 주변 환경의 상호작용의 결과로 설명한다. 이 이론에서는 동작을 제한하는 요소로 인간의 물리적인 신체 조건 및 인체측정학적 요소를 꼽는다. 또한 근육 및 관절이 개별적, 독립적으로 동작되지 않고 “synergy” 라고 일컬어지는 어떠한 조합으로써 제어된다고 가정하며 이에 대한 근거를 제시한다.

본 논문의 목적은 이러한 이론을 바탕으로 스마트폰 조작 중 그립 및 엄지의 조작을 포함하는 손 동작을 분석하는데 있다. 동작을 분석함에 있어 손의 물리적인 인체측정학적 요소를 동작을 제한하는 제한 조건(constraint)으로 설정하였다.

이러한 목적을 달성하기 위해, 첫째, 스마트폰 사용과 관련된 손의 치수를 설정하고 손의 형태를 분류하였다. 연구 목적에 가장 알맞은 분류 결과를 도출하기 위해 일반적으로 사용되는 k-means, fuzzy c-means 및 LPA의 세 가지 분류 기법을 적용

하였고 그 결과를 비교하였다. 이 후 손의 동작 분석에 이렇게 분류된 손 타입이 미치는 영향을 분석하였다.

둘째, 스마트폰 그립을 정의하기 위해 기존 그립 분류 체계를 검토하고 스마트폰 그립이 어떠한 기존 그립 형식에 해당되는지 확인하였다. 문헌 분석 결과, 스마트폰 그립이 기존 분류 체계에 정확히 해당하지 않아 기존 분류 체계를 재 정의하는 새로운 방법을 시도하였다. 1) 실험을 진행하여 muscular synergy와 postural synergy를 도출하였고, 2) 기존 그립 형태를 synergy를 기반으로 재 분석하였으며, 3)스마트폰 그립이 기존 그립 분류 체계에서 어디에 해당되는지 확인하였다. 마지막으로 스마트폰 그립을 포함한 새로운 그립 분류 체계에 손 타입이 영향을 미치는지에 대한 여부를 파악하였다.

셋째, 스마트폰 그립 및 엄지 조작을 muscular synergy와 postural synergy 차원에서 분석하였다. 가장 대표적인 스마트폰 조작 방식인 tapping과 dragging 과업을 선택하였고, 각 과업은 세부 수준으로 나누어 과업 수행 결과를 분석하였다.

인간 동작을 분석하는 것은 동작 제어 전략을 이해하는데 중요하다. 본 연구 결과는 다음과 같은 연구 의의를 가진다: 스마트폰을 사용할 때의 손 동작에 대한 이해에 도움을 준다; 스마트폰을 포함한 소형 터치스크린 기기를 위한 상호작용 및 인터페이스를 설계하는데 활용될 수 있다; 자유도 중복 문제와 관련 있는 로봇 손과 인공 손을 설계하는데 본 연구에서 정의된 synergies가 적용될 수 있다.

주요어: human hand, handheld touchscreen devices, grasp taxonomy, hand classification, muscular synergy, postural synergy

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