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Multi-Element Synergies in Force Production and Release Task

- Archery Shooting-Like Action -

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Abstract

The human body has more degrees of freedom (DOF) than the minimum number of elements required to accomplish a certain task. This is called motor redundancy, and the human body has characteristics of motor redundancy in various hierarchies. Therefore, the mechanism by which the CNS controls redundant DOFs is one of the most actively studied areas of human movement science. The purpose of this study is to understand the role of the human multi-element control mechanism (synergy) characterized by redundancy in terms of actual performance. To this end, we conducted four experimental studies that simulated the shooting action of archery, a task aimed at accurate and consistent performance. In the first three studies (chapter 3, 4, 5), we examined whether the hierarchically redundant human motor system can be understood as a motor abundance that plays a positive role for the performance (accuracy and precision) from the synergy point of view. And in the fourth study (chapter 6), we examined how the performance of the task is related to the human multi-element control in the feedforward form. An analytical method based on the uncontrolled manifold hypothesis (UCM) confirmed the interaction patterns between each element (each hand, each finger, or each muscle group), and this has been performed correlation analysis with the accuracy and precision (consistency) of the task. As a result, increasing kinetic degrees of freedom increases multi-finger synergy, which has a positive effect on improving task performance, and the positive effects of this increase can also be extended to hierarchical tasks. Additionally, the anticipatory mechanism of abundant degrees of freedom has a positive effect on the consistency of the task. This confirms the theory that the characteristics of the human motor control system, motor redundancy, is not a computational burden of the central nervous system but a positive contributor to task performance through various solutions.

Keyword: motor redundancy, motor synergy, anticipatory synergy adjustment (ASA), uncontrolled manifold (UCM) hypothesis, archery
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Table of Contents

List of Tables

Chapter 3

List of Figures

Chapter 3

Chapter 4

Chapter 5

Chapter 6

Chapter 1. General Introduction

Although human redundancy has been understood as a computational problem from a mechanical point of view (Arimoto, Tahara, Bae, & Yoshida, 2003; Cheng & Orin, 1991; Company, Marquet, & Pierrot, 2003; Xia, Feng, & Wang, 2005), several recent studies have suggested that the central nervous system (CNS) can flexibly utilize redundant degrees of freedom (DOFs) for successful task performance (Karol, Kim, Huang, Kim, Koh, Yoon, & Shim, 2011; Latash, Scholz, Danion, & Schoner, 2001; Li, Latash, & Zatsiorsky, 1998; Scholz, Danion, Latash, & Schoner, 2002). The mechanism by which the CNS controls redundant DOFs is one of the most actively studied areas of human movement science. Bernstein (1967) introduced the concept of motor synergy as a mechanism by which the CNS controls redundant DOFs. Synergy is a phenomenon in which element variables (commands) with redundant DOFs co-vary to stabilize the primary performance variable of a particular task. This study was conducted to understand the concept of motor synergy in relation to the effective execution of specific tasks.

This study was conducted in four experimental studies. We examined in the first to third studies (chapter 3, 4, 5), whether the hierarchically redundant human motor system can be understood as a motor abundance that plays a positive role for the performance (accuracy and precision), and the mechanism by which such a positive result can be obtained was examined from the synergy point of view. And in the fourth study (chapter 6), examined how the performance of the task is related to the human multi-element control in the feedforward form. For this purpose, this study focuses on the hand, which is a representative multi-element system of the human

body. And we reproduce the shooting operation of the archery in which the force control of each finger is closely related to the performance. We can understand the role of human multi-element control mechanism in terms of actual performance through the results of this study.

Chapter 2. Literature Review

2.1. Problem of degrees of freedom (Motor redundancy)

The human body is a system that can satisfy the same performance through various combinations and trajectories of elements, and this is due to the fact that the elemental variable has relatively large degrees of freedom (DOFs) compared to the performance variables to satisfy the task. The problem of how efficiently these redundancy problems are controlled by the central nervous system (CNS) is one of the major issues of interest in human movement science.

Many previous studies of the past have explained that excess DOFs act as a control problem in the CNS (Arimoto et al., 2003; Cheng & Orin, 1991; Todorov & Jordan, 2002; Xia et al., 2005), and therefore, the system tries to restrict or reduce the number of degrees of freedom being controlled. And recent studies have reported that these redundant degrees of freedom interact with each other in order to stabilize important performance variables (Park, Jo, Lewis, Huang, & Latash, 2013). In other words, rather than computing a unique solution to satisfy the task, the CNS might utilize a family of solutions to fulfill the task requirements. This concept can be explained by the principle of motor abundance that understands motor redundancy as a motor abundance rather than a control problem (Gelfand & Latash, 1998; Latash, 2000). The various types of motions made possible by redundant elements interact with each other to satisfy the task, and for this particular purpose, the form in which each element interacts can be defined as synergy (Latash, Danion, Scholz, Zatsiorsky, & Schoner, 2003).

Although many previous studies have described the positive aspects of motor redundancy in the concept of motor abundance, there have been very few studies that investigated the relationship between the amount of motor redundancy and synergistic actions of multiple effectors (Karol et al., 2011). In Karol et al. (2011)'s previous study, which compared the interactions of the fingers while changing the DOFs of the fingers, they performed finger-pressing tasks by varying the DOFs of two to four fingers. As a result, force stabilizing synergy in all conditions (details of synergy quantification will be explained later), four finger combinations showed stronger force-stabilizing synergies than the two and three finger combinations. This phenomenon can be interpreted as a result of supporting the concept of the principle of abundance.

When sufficient DOFs are provided, the CNS can simultaneously stabilize the total force and the total moment. This has been confirmed in several studies through multi-finger pressing tasks or prehension tasks (Shim, Latash, & Zatsiorsky, 2005; Shim, Olafsdottir, Zatsiorsky, & Latash, 2005; Shim, Park, Zatsiorsky, & Latash, 2006) and also reported that the force and the moment were stabilized together even when moments are not provided as feedback (Gorniak, Zatsiorsky, & Latash, 2007; Latash, Scholz, & Schoner, 2007).

On the other hand, the two-finger combination is a special case. If we assume that there is no change in the force application point of the two fingers, Force and moment stabilizing synergy have a negative correlation, this is a condition that cannot simultaneously stabilize two variables (force & moment). the three-finger combination and the four-finger combination with an unstable pressing setup have a tendency to stabilize the total moments, even in time-invariant tasks (Karol et al., 2011; Latash, Kang, & Patterson, 2002; Latash et al., 2001). And three-finger and

four finger combinations, which provided sufficient DOFs to simultaneously stabilize the two variables, did not show a statistically significant difference in moment stabilizing synergy (Karol et al., 2011). Karol et al. (2011) suggesting that, if the feedback is provided, the possibility of moment stabilizing synergy in all combinations.

2.2. Motor synergy

Bernstein was first to introduce synergy as a solution to the problem of excessive degrees of freedom (Bernstein, 1967). In other words, Synergy can be defined as co-varied adjustments of commands to stabilize performance variables (Park et al., 2013). According to previous studies, the patients with brain damage showed a significant change in overall performance, but the synergy index showed similar values between ipsilesional (relative spared) and contralesional (strongly affected) limbs (Park et al., 2013). these studies suggest that the synergy patterns depend more on the proper functioning of subcortical structures.

The characteristics of motor synergies can be defined in the following three ways (Latash et al., 2007). First, Elements of the system should contribute to a particular task. Second, there should be error compensation among the elements to perform a task. And third, the behavior of the elements should be dependent upon the task.

2.2.1. Error compensation

For uncorrelated data, the sum of the variance is equal to the variance of the sum (the Bienaime equality). However, if the sum of variances ($\Sigma VarF_i$) of each finger is larger than the variance of the resultant force ($VarF_{TOT}$) when performing a multi-finger pressing task, one may conclude that there is predominantly negative covariation among finger forces such that they partly compensate for each other's errors with respect to the total force profile (Latash, Li, & Zatsiorsky, 1998; Latash et al., 2001; Scholz et al., 2002). This phenomenon is one of the representative features of the concept of human multi-elemental synergy.

According to Shinohara, Latash, and Zatsiorsky (2003), both young and elderly subjects show no error compensation among the fingers at low forces. However, when more than 5 N, significant error compensation ($\Sigma VarFi > VarF_{TOT}$) appears regardless of age or individual maximum voluntary contraction (MVC) force value. The authors point out that the environment in daily life is the same regardless of the person's age or force generating abilities, also, it is suggested that error compensation due to synergy may be related to tactile feedback. Latash et al. (2002) also reported that visual feedback does not have any effect on multi-finger pressing synergies in time variant tasks. Karol et al. (2011) explains that tactile feedback may have positively influenced multi-finger synergy, In the task of increasing the DOFs of the fingers, additional tactile feedback from the finger tips could be expected to increase the synergy index. Shim, Latash, and Zatsiorsky (2003) reported that the multi-finger synergy index showed a negative value at the beginning of a multi-finger pressing task and then turned to a positive value after a certain period of time. They considered the effect of tactile feedback from the finger tips as the reason. As a result of these

experiments, they found that the faster rate of force production, synergy index (ΔV) turned positive at higher forces. In other words, the critical time (the time it took ΔV to turn positive) in that study did not correspond to a fixed force level. The authors understand that multi-finger synergy is required for a certain amount of time.

On the other hand, the mechanism of error compensation is mainly explained by the central back coupling model (Latash, Shim, Smilga, & Zatsiorsky, 2005). The central back coupling model focuses on Renshaw cells (Rothwell, 1987), which is a representative neurophysiological structure of the neural mechanism of self and lateral inhibition among the elements. Synergistic responses by Renshaw cells have also been reported to occur in different muscles (Karol et al., 2011).

2.2.2. Task dependency of the synergy

Another representative features of the concept of human multi-elemental synergy is task-dependency (Latash, 2008). In other words, the form and magnitude of the synergy vary depending on the nature of the task. previous studies have reported that the control mechanism of redundant elements (fingers) varies depending on the type of task. Latash, Shim, and Zatsiorsky (2004) reported that the force of each finger shows a pattern of negative covariance in the task of slowly increasing the force by using multiple fingers, but a positive covariance pattern in the case of fast force generation task (Latash et al., 2004). In other words, the control mechanisms of the multiple factors can vary depending on how long it takes to perform the task. For example, it has been hypothesized that time variant tasks like ramp force production need feedback control, while rhythmic tasks like oscillatory force production tasks are controlled more by using a feed-forward mechanism (Wei,

Dijkstra, & Sternad, 2008). And If the target task is not to control the magnitude of the resultant force of the fingers but rather to control the moment of force generated by both fingers, each finger force will show a pattern of positive covariation rather than negative covariation (Latash et al., 2003). As such, depending on what performance variable the system is trying to stabilize, also the control mechanisms of the multiple factors can vary (Latash, 2008; Latash et al., 2003; Latash et al., 2004).

As mentioned above, there are two performance variables that are considered important for stable execution of multi-finger pressing and prehension tasks. the total force generated by the individual fingers and the total moment of forces produced by individual fingers (Kang, Shinohara, Zatsiorsky, & Latash, 2004; Shim, Lay, Zatsiorsky, & Latash, 2004; Shinohara et al., 2003)

The CNS can simultaneously stabilize the resultant force and the resultant moment through a kinetic abundance of multi-fingers, under conditions of more than three fingers during a multi-finger pressing or prehension task. Simultaneous stabilization of these forces and moments of force can be the evidence of the principle of abundance by the CNS (Latash, 2000; Latash & Zatsiorsky, 2009)

On the other hand, Karol et al. (2011) reported that moment stabilization error was large when subjects did not provide feedback on moment stabilization. which is explained by the fact that the primary task is force stabilization. The results can be interpreted as a result of task-dependent motor synergy characteristics because task is the stabilization of the force (Latash et al., 2007). In other hand, when the force stabilization is presented as a task, the moment also tends to stabilize, however, when the moment stabilization is presented as a task, there is no force stabilization synergy (Zhang, Zatsiorsky, & Latash, 2007). These results experimentally confirm that the time profile of moment stabilization is stronger than force stabilization. In daily life,

moment stabilization by the interaction of each finger force is relatively more important as it relates to the rotational equilibrium of the hand-held object when we perform actions such as lifting a water cup. Shim et al. (2007) also presented an experiment in which a mechanical perturbation was applied to a hand holding an object, which suggested that CNS may consider rotational equilibrium control more than grasping stability control. In these respects, these results suggest that the internal constraint on moment stabilization is probably a stronger implicit than the internal constraint on force stabilization as a default condition due to the experience of everyday life (Zhang et al., 2007).

2.2.3. Hierarchy of the synergy

The redundancy of DOF spans multiple levels, and the synergy also exists across various hierarchies. For example, if we are performing a prehensile task, there is a synergy of the lower hierarchy between the fingers, and the synergy of the higher hierarchy between the thumb and the virtual finger (the sum of the effects of each finger). Similarly, when the task using both hands is performed, the synergy of the lower hierarchy between the fingers, and the bimanual synergy between the two hands. The hierarchical control theory of synergy at these one-hand or two-hand levels was mentioned in several studies (Domkin, Laczko, Djupsjobacka, Jaric, & Latash, 2005; Gorniak et al., 2007; Scholz & Latash, 1998; Shim, Olafsdottir, et al., 2005; Zatsiorsky, Gao, & Latash, 2003).

Thus, synergy across multiple hierarchies takes an input from an upper hierarchy to produce an output, which has a structure that acts as input to the lower hierarchy (Gorniak et al., 2007). In general, each synergy that exists across multiple

hierarchies can be expected to work together to achieve a common goal. On the other hand, Gorniak et al. (2007) reported that multi-finger synergy in one hand was very weak when both hands were involved in the task through the multi-finger task of both hands. This is an interesting result when compared to the tendency to have very strong multi-finger synergy when participating in a one-handed task. The authors explained that two synergies at two hierarchically different levels can work together for one goal at the same time, which is not easy for the controller. The authors explained that it is not easy for the controller to have two synergies at two different levels working simultaneously for one goal at a time.

2.3. UCM hypothesis

Several previous studies used the uncontrolled manifold (UCM) approach to quantify the synergy of multi-fingers. The UCM hypothesis is based on the principle of motor abundance that controls key performance variables through the advantage of redundant DOFs in performing repetitions of the tasks instead of selecting a unique solution (Scholz & Schoner, 1999; Scholz, Schoner, & Latash, 2000). The UCM approach quantifies synergy in space, which can be formed by the combination of each element (finger). The synergy can be quantified by relative variance on subspace that does not affect performance variable (V_{UCM}) and subspace which is an error for performance variable (V_{ORT}). Because the synergy index is a variable that is influenced by both components, V_{UCM} and V_{ORT}, the change in the synergy index cannot be attributed to a change in one component (Karol et al., 2011). Therefore, although the synergy index itself cannot be a criterion for assessing the completeness of task performance, it can provide information on how aggressively the CNS uses

motor redundancy. The intentional increase in V_{UCM} can be evidence that the system can explore a variety of solutions under abnormal conditions or uncertainty conditions (Freitas & Scholz 2009; Yang, Scholz, & Latash, 2007). A series of recent studies documented that the changes in multi-finger synergies may occur due to aging or neurological disorders (Park et al., 2013; Park, Singh, Zatsiorsky, & Latash, 2012; Park, Sun, Zatsiorsky, & Latash, 2011; Reisman & Scholz, 2006).

Some studies have reported changes in the synergy index due to training. Domkin, Laczko, Jaric, Johansson, and Latash (2002) studied kinematic synergy through reaching tasks. The authors reported a decrease in the synergy strength due to the relatively large reduction of V_{UCM}, through practice. However, a follow-up study (Domkin et al., 2002) has reported that V_{UCM} and V_{ORT} decrease with synergistic index in more complex tasks. These results show that the change in the synergy index by practice is related to the complexity of the task.

In some previous studies that observed changes in synergy following practice, they reported an increase in the synergy index at the beginning of practice and then a decrease (Latash et al., 2003). In the study, subjects showed a very low V_{ORT} at the moment of force on the multi-finger force production task with the mid-practice. As practice continued, subjects showed control strategies that reduced V_{UCM} only, without changing V_{ORT}. This study suggests that the stages of motor learning and the stages are associated with the emergence of changes in appropriate synergies. This improvement in performance through practice may be related to the optimization of variables (i.e., such as energy expenditure, fatigue, etc.) that are not directly related to performance. These additional constraints can be expressed in a form that limits the space of acceptable solutions while maintaining the same performance (i.e., limit the amount of V_{UCM}), This is related to a decrease in the synergy index due to practice

(Latash, 2010).

The UCM analysis is typically performed within a linear approximation for the multi-finger pressing force production tasks using the null-space of the Jacobian matrix as a local approximation of the UCM (Latash et al., 2007; Scholz & Schoner, 1999). And for UCM analysis, a large number of trial data should be collected, assuming that the subject did not change the control strategy while performing the task. It is, however, difficult to apply UCM analysis to people with movement disorders (Scholz, Kang, Patterson, & Latash, 2003). Therefore, Scholz et al. (2003) applied a UCM analysis within a single trial to obtain significant results from patients who have difficulty in obtaining enough trial data and reported some similar results with the UCM analysis across trials.

2.3.1. multi/single trial UCM

In general, the synergy of individual finger forces to stabilize a particular performance variable is assumed to be due to the neural control level of the lower hierarchy (timing or synergy level) based on the Schöner's scheme (Latash et al., 2002; Latash et al., 2001; Scholz et al., 2002; Schoner, 1995). However, Major changes in the sharing pattern without a change in the total force profile are expected to lead to such negative co-variations between finger forces meaning that error compensation can occur at the higher (motor planning) level. Scholz et al. (2003) also explained that both the higher hierarchy (motor planning level) and the lower hierarchy of the neural level of control are involved in error compensation.

Li et al. (1998) explain that individual finger force sharing, commonly known to control at higher neural levels, is more prominent across trials. So the authors also

presented a single-trial UCM analysis (UCM analysis within-trial method) that utilized each data point in a trial as well as a general multi-trial UCM analysis (UCM analysis across trials method) using multiple trials. in other words, the results calculated by the two UCM analyzes can reflect different degrees of each neural control level.

Both methods have different characteristics. UCM analysis within-trial has the advantage of achieving significant results for multi-finger interaction through a small size of data. In fact, Scholz et al. (2003) analyzed the UCM analysis within-trial method to apply the UCM approach to patients who have been unable to maintain long-term concentration or participate physically in long-time experiments and reported some similar results with the UCM analysis across trials method. On the other hand, the advantage of the UCM analysis across the trials method is that we can observe the change of synergy index over time series because we use the data points of the same time period of many trials. The most prominent phenomenon we can confirm through these characteristics is anticipatory synergy adjustment (ASA).

2.4. Anticipatory synergy adjustment (ASA)

Anticipatory synergy adjustment (ASA) can be understood as a strategic control mechanism of the central nervous system (CNS) that regulates synergy to stabilize key performance variables when rapid changes in the commend are needed. The feature of ASA is that it only changes the co-variation pattern between elemental variables and does not affect the average value of the performance variable. Previous studies have shown that the synergy index is reduced from 200 to 250 ms before the intentional movement or the perturbation that can predict the time (Klous, Mikulic,

& Latash, 2011; Krishnan, Aruin, & Latash, 2011; Olafsdottir, Yoshida, Zatsiorsky, & Latash, 2005; Olafsdottir, Kim, Zatsiorsky, & Latash, 2008) and This can be observed through UCM analysis across trials according to the central back-coupling hypothesis (Latash et al., 2005). ASA is related to the stability properties of the performance variable, and there would be an advantage that we can flexibly respond to changes in the task through mechanisms that reduce the stability for the performance variables in advance. Because the high stability of a variable could be counterproductive if a person plans to change the variable quickly.

According to the central back-coupling hypothesis, a hierarchically higher controller controls two neural variables. One of them controls the magnitude of the main performance variable associated with the nature of the task, and the predictive change in the specific behavior or perturbation of this variable leads to an anticipatory postural adjustment (APA). APA refers to background activity of postural muscle that appears before predictable perturbation or intentional movement (De Wolf, Slijper, & Latash, 1998).

The difference between APA and ASA is that APA has been identified only in the direction of anticipating the physical effect (Forssberg & Hirschfeld, 1994; Krishnamoorthy & Latash, 2005). If we know the exact time of an action or perturbation, but we do not know the direction, then APA may be rather disturbing. In fact, if the force/moment change is different from the predicted direction, APA worsens the effect of that perturbation. On the other hand, ASA cannot change the performance of a specific performance variable or perturbation but can facilitate operation regardless of direction. Zhou et al. (2013) reported that the timing and magnitude of the ASA were the same when the direction of perturbation was precisely known or not.

2.5. Finger enslaving

The UCM hypothesis is often used to analyze the interaction of each finger during multi-finger force producing tasks (Latash et al., 2002; Latash et al., 2001; Scholz et al., 2002). These studies assume that the hypothetical control variable called force mode (Danion et al., 2003) is an element variable considering the interdependency between the fingers. Thus, "voluntary" but "unintended" finger actions (Park & Xu, 2017) generated by independent neural commands for the action of one finger are expressed in terms of finger enslaving. One of the characteristics of a finger is that the relationship between the forces generated by the master finger and slave fingers are nearly linear within a broad range of forces (Li et al., 1998; Zatsiorsky, Li, & Latash, 2000). The mechanism of the finger enslaving can be explained by two reasons, central reason and peripheral reason.

2.5.1. Central reason of finger enslaving

The central reason for the enslaving include divergence and convergence of cortical projections due to overlapping digit representation in the hand area of the primary motor cortex (Schieber, 1990; Schieber & Hibbard, 1993). Some previous studies reported a positive correlation between ensuring and maximum voluntary force of fingers (Shinohara et al., 2003). (Danion, Latash, Li, & Zatsiorsky, 2000, 2001). These results are in contrast to previous studies that showed higher enslaving in individuals with neurological disorders (Jo et al., 2016; Park, Lewis, Huang, &

Latash, 2013; Park, Wu, Lewis, Huang, & Latash, 2012). The results of higher enslaving, despite the relatively small maximum voluntary force of fingers in the persons with neurological disorders, provide evidence for the mechanism by which Enslaving is caused by the central factor (Park, Lewis, et al., 2013; Park, Lewis, Huang, & Latash, 2014)

2.5.2. Peripheral reason of finger enslaving

For peripheral reasons of enslaving, the flexion movements of the fingers are usually caused by intrinsic muscles in contact with the proximal phalanges, extrinsic muscles in the medial and distal phalanges and multi-digit tendons (Landsmeer & Long, 1965). Long flexors of human digits cannot independently contract, and this feature causes each finger to be incapable of completely independent force generation even in isometric conditions (Kilbreath & Gandevia, 1994; Zatsiorsky et al., 2000).

2.6. Movement variability in sports field

In the past, the main goal of deliberate practice in sports was considered to minimize the deviations of performance from the internalized expert model or template (Ericsson, Krampe, & Teschromer, 1993), and many coaches and leaders felt that this type of training method could improve the consistency of movement execution and hence the accuracy of the action. In addition, many biomechanists have also defined skilled motor performance as a behavior with small variability (Glazier, Davids, & Bartlett, 2003). As such, it was common in the sports field to

regard the consistency and stability of movement as essential characteristics of the performance.

However, Handford (2006) comments that some variables may require performance to be stable only if other variables are allowed to vary. Many studies have focused on compensatory mechanisms between these fluctuating execution variables, and Bootsma and van Wieringen (1990) defined this as compensatory variability. Bartletti, Wheat, and Robins (2007) also demonstrated that the freeing of biomechanical DOFs plays a positive role in assisting the compensatory strategy of skilled performers.

A variety of studies have shown that movement variability affects positively in a sports field. Button, MacLeod, Sanders, and Coleman (2003) confirmed that the inter-trial variability of basketball shooting behavior varies with skill level. According to their study, 'compensation variability' appeared to minimize the variability of the release parameters in the elbow and wrist joints of the skilled performers. variety of stone knapping studies has also concluded that activation of a greater number of DOFs can indicate a level of expertise, and they also explained that experts achieve their goal by generating consistent kinetic energy through the variability of movement kinematics. Bernstein (1967) also noted that as Golfer's skill improves, swing characteristics evolve into more flexible control of joints and muscles. As such, we should accept that variability is crucially important in sports performance (Bartletti et al., 2007)

Chapter 3. Effect of kinetic degrees of freedom of the fingers on the task performance during force production and release

Chapter 3 contains the following original paper reprinted by the permission from Korean Studies Information (KSI): **Kitae Kim**, Dayuan Xu, Jaebum Park (2018) Effect of Kinetic Degrees of Freedom of the Fingers on the Task Performance during Force Production and Release: Archery Shooting-like Action. ***Korean Journal of Sport Biomechanics, 27***(2), 117-124.

3.1. Introduction

The human body is a system capable of achieving the same task via various ways, which is a result of the component variables having relatively more degrees of freedom (DOF) than the performance variables. Hence, the efficiency of the strategies of the central nervous system (CNS) to control redundant components is a major area of research in human movement science. Such abundance of DOF spans multiple levels, from joints and muscles to motor units, and recent studies suggest that the abundant DOF interact to stabilize the major performance variables (Park, Jo, et al., 2013). In other words, various forms of movement enabled by redundant components are a result of interaction among each component to satisfy a task, and the method of this interaction may be understood with the principles of body control by the CNS (Latash et al., 2003).

Each finger may be considered an individual component that can produce force, and kinetic redundancy occurs when two or more fingers are used to produce force. When we view the redundancy problem from engineering and mathematical perspectives, this problem ultimately incurs computational burden on the control system; hence, multiple studies are underway to identify the solutions to the redundancy problem (Arimoto et al., 2003; Cheng & Orin, 1991; Xia et al., 2005). In terms of human movement, the redundancy problem partially compensates the errors in which each component (finger) affects the performance outcome (resultant force). That is, redundancy does not incur a burden on the control system of the CNS but instead poses an advantage for the system to flexibly rectify the errors caused by each component (Gelfand & Tsetlin, 1961; Latash et al., 2001; Li et al., 1998; Scholz et al., 2002).

Archery is a sport that involves the use of multiple fingers. In terms of the finger movement during release, it may be an example of kinetic redundancy experienced in the sports setting. The sport demands archers to consistently maintain the force on the bowstring and aim for the target by stably controlling the force produced by multiple fingers. In the actual game, clickers are used to control the distance by which the string is drawn, and archers are also demanded to be equipped with the ability to quickly respond to the clicker and release the finger (Leroyer, Van Hoecke, & Helal, 1993). Therefore, the shooting movement in archery is a complex task comprising two goals, namely stabilization of static force and quick release of the force. Previous studies report varying outcomes in relation to the type of task targeted by the control mechanism of the abundant components (fingers). The control mechanism of multiple components may differ depending on the performance variable that the system is aiming to stabilize or depending on the time required to

perform the task (Latash, 2008; Latash et al., 2004). In this context, archery shooting is a task to be achieved by two different mechanisms to control the redundant fingers.

This study aimed at investigating the effects of change in DOF on the performance outcome. As previously mentioned, fingers, as redundant components, do have positive aspects, as they may compensate errors caused by one another and stabilize the outcome, but they also pose a challenge in quickly responding to the changes of force. Thus, this study seeks to understand the control mechanisms of multiple components and identify the effects of DOF on task performance in archery shooting-like action. We will test the following hypotheses in this study. First, increasing the DOF of fingers will reduce the error of force produced by the fingers. Second, it will increase the time required to release the force. Third, increasing the DOF of the fingers by reducing the error of force and increasing the release time will not have an impact on the outcome of performance (accuracy and precision).

3.2. Methods

3.2.1. Participants

Eight right-handed male adults (age: 29.63±3.02 years, height: 1.73±0.04 m, weight: 70.25±9.05 kg) participated in this study. None of the participants had a disease that may affect the functions of the arms, hands, and fingers. All the participants had adequate practice to familiarize themselves with the task before beginning the main experiment. This study was approved by the institutional review board (IRB No. 1703/002-006).

3.2.2. Apparatus

The task to be studied is a multi-finger force production and release task. To deliver steady levels of force throughout the experiment, the participants underwent a maximum voluntary contraction task prior to the study. Maximum voluntary contraction was measured by using four horizontally fixed piezoelectric transducers (208C02, PCB Piezotronics, Depew, NY). For the main task of the study (multi-finger force pro- duction and release task), four 6-axis force/torques transducers fixed onto a metal frame (Nano-17, ATI Industrial Automation, Garner, NC) were used (Figure 3-1). The transducers were oriented such that the direc- tion of the press is perpendicular to the direction of gravity to eliminate the impact of gravity on the fingers when producing force. A transducer cap (poly lactic acid) was attached to each transducer to facilitate the natural force production and release (Figure 3-1).

While performing the task, the participant sat upright on the chair, and the right shoulder joint was positioned to be at approximately 45° flexion, 45° abductions, and 10° internal rotations (Figure 3-1). The *x*-, *y*-, and *z*-axes of the transducer represents the mediolateral, superoinferior, and anteroposterior directions with reference to the participant. Analog signals from the transducers were digitalized and transmitted to the computer by using an analog-digital converter (NI USB-6225, National Instruments, Austin, TX). During the experiment, a program that we developed using a programming software (LabVIEW 2015, National Instruments, Austin, TX) was used to collect data and provide visual feed- back to the participants.

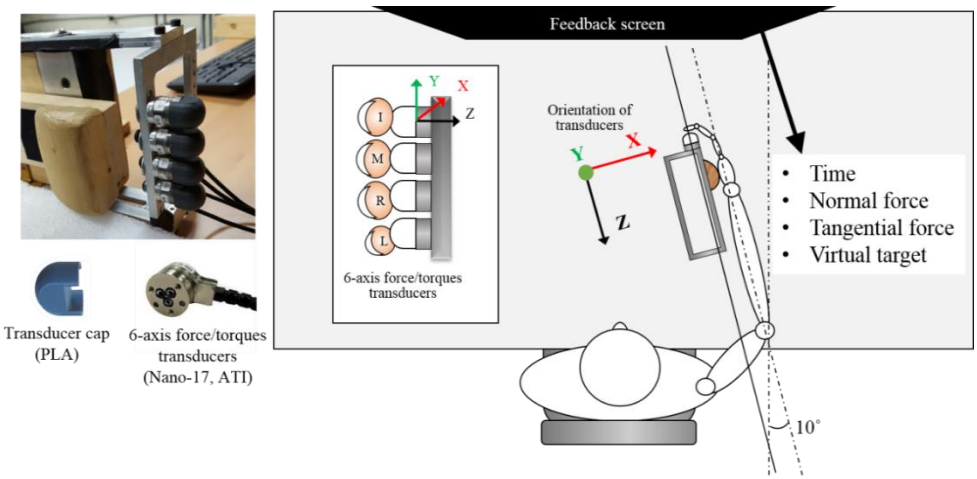

Figure 3-1. Apparatus for the multi-finger force production and release task. Four 6-axis force/torque transducers are fixed to a metal frame, and the front monitor provides feedback

3.2.3. Measurement

For the maximum voluntary contraction task, the participants placed four fingers on the four transducers that are horizontally fixed onto a metal plate and performed maximum isometric contraction for 5 seconds without counter movement. While the participants performed the trial task, the force values for each finger (MVC_i, i = {index, middle, ring, little}) were obtained at the peak resultant force (MVC_{TOT}). Two trials were performed, and the average of the values were used.

The main task (multi-finger force production and release task) emulates the aiming and release movements of archery. For this task, each participant presses on the transducers aligned along the *y*-axis with three combinations of degrees of freedom (index-middle [IM], index-middle-ring [IMR], index-middle-ring-little [IMRL]) as if pulling (aiming) and quickly releasing their fingers from the transducers (release). This task is divided into the aiming and release phases. The

aiming phase comprises the first 5 seconds, where the anteroposterior (*z*-axis), mediolateral (*x*-axis), and superoinferior (*y*-axis) force of pre-established magnitude is produced and steadily maintained, while the release phase comprises the subsequent 5 seconds, where the fingers are released as quickly as possible. The magnitude of the force that the participants must maintain within the first 5 seconds is set based on the magnitude of the energy stored in the bow. The anteroposterior force (*z*-axis) was set to 50% of the MVC_{TOT} (maximal force produced by four fingers), and the mediolateral and superoinferior forces were set to 0 N. In other words, the conditions of the force values for the aiming phase were set equally for all three finger combinations, and the virtual target was considered hit when no errors were found in the force values and the force release takes the form of a step function (drop to 0 N without time delay). The projectile projected through the release motion is a virtual object; it is a point mass that only has mass and no volume, and gravity is the only external force acting on the projectile. The onset of the release motion is self-paced by the participant and not induced by an external cue. Each participant is instructed to perform 25 trials of the task per condition (finger combination) with a minimum rest of 5 minutes between each condition and 10 seconds between each trial. The front monitor provides time information to alert participants of the phase during which a constant force must be maintained and the phase during which the force may be released, information about the force values for each component that should be maintained during the aiming phase, and information about the location that the released projectile hit on the virtual target.

3.2.4. Data processing

Data were analyzed by using customized MATLAB codes (MathWorks Inc., Natick, MA, USA). All the measured force values were filtered with a zero-lag fourth-order low-pass Butterworth filter (cutoff at 10 Hz). The coordinates of the projectile on the virtual target were set to be deter- mined by the initial velocity (speed and direction) of the projectile, and the initial velocity was assumed to be influenced by the loss of energy at the release of force. That is, energy is stored on the virtual bow during the aiming phase, and all stored energy is used for moving the virtual projectile to the target without loss if the release is made without time delay. The initial velocity of the projectile was calculated based on the magnitude of the force measured at the onset of release, modulus of elasticity (0.7 N/m) of the virtual bowstring, and weight of the virtual projectile (1 kg). Energy loss at force release was calculated under the assumption that the amount of impact on the initial velocity equals the integral of force during the release phase (Equation 3-1). In this experiment, we assumed that the elastic energy stored in the bow is converted to the kinetic energy of the projectile without loss, so the initial velocity of the projectile was calculated as per the equation below. Anteroposterior, mediolateral, and superoinferior velocity components were each calculated, and the acceleration of gravity for the superoinferior velocity was set to -9.81 m/s2.

$$V_0^j = \frac{F_{t0}^j}{\sqrt{k \cdot m}} - \frac{\int_{t0}^{t1} F^j(t) \cdot dt}{m} \qquad \text{(Equation 3-1)}$$

, where, j = {x, y, z}, k and m represent the coefficient of elasticity of the virtual

bow (0.7 N/m) and the mass of the virtual ball as a particle (1 kg), respectively. t_0 and t_1 stand for the onset time of release and the time of completion of force release after t_0, respectively. The horizontal distance from the release point to the virtual target was set at 0.7 (m/N) × ΣMVC_i.

3.2.4.1. Definitions of the phases for analysis

In the multi-finger force production and release task, the onset of release was defined as the point equal to the 5% of the maximum value of the first derivative (maximal change) of the anteroposterior component (*z*-axis) of the resultant force produced by the fingers participating in the task (Olafsdottir et al., 2005). Data from two phases were analyzed. The first phase, which is the aiming phase (where the force is maintained), was defined as the period between -1500 ms and -500 ms with reference to the onset of release (Equation 1a). The second phase, which is the release phase, began from the onset of release to the point at which the resultant forces of the fingers reached 0 N (Equation 3-1b).

3.2.5. Variables for analysis

The variables for analysis in this study were as follows: 1) finger force sharing pattern in the aiming phase, 2) root mean square error (RMSE) of force to the reference force in three axes at the aiming phase, 3) the duration of the release time (RT), and 4) the accuracy index (ACI; Equation3), and precision index (PRI; Equation 3-4) of the virtual firing position. The finger force sharing pattern in the aiming phase was presented as the mean force values in the aiming phase. RMSE, which represents the deviation from the reference force in the aiming phase, was

calculated as per Equation 2 and was standardized based on each reference force.

$$RMSE_{NORM}^{j} = (\sqrt{\sum^{n} F^{j} - F_{REF}^{j})^{2} / n}) / F_{REF}^{j} \qquad \text{(Equation 3-2)}$$

, where, j = {x, y, z}, and n represents the number of data samples during steady-state force production. F and F_{REF} represent the produced total forces by the participants and the total reference force, respectively.

Releasing time (RT) is defined as the duration of the release phase. The ACI is the mean displacement of the virtual projectile from the center of the virtual target, and the PRI is the mean displacement of the virtual projectile in the given trial from the mean coordinates of the virtual projectile in previous trials (Kim et al., 2016; Koh et al., 2016). Each variable is calculated as per Equations 3-3 and 3-4.

$$ACI = \frac{\sum_{i=1}^{n} \sqrt{(x_i - x_{CENT})^2 + (y_i - y_{CENT})^2}}{n} \qquad \text{(Equation 3-3)}$$

$$PRI = \frac{\sum_{i=1}^{n} \sqrt{(x_i - x_{MEAN})^2 + (y_i - y_{MEAN})^2}}{n} \qquad \text{(Equation 3-4)}$$

, where, i= each trial, {x_i, y_i}: x- and y-coordinate of the hitting position for each trial, {x_{CENT}, y_{CENT}} = x- and y-coordinate of the center of the virtual target (0 mm), {x_{MEAN}, y_{MEAN}} = x- and y-coordinate of the mean hitting position for all trials.

3.2.6. Statistical analysis

Statistical analyses were performed by using the SPSS 21.0 (IBM, Armonk, NY)

software, and repeated-measures analysis of variance (ANOVA) was performed to verify the statistical differences among the variables. The *Finger*-related factors (4 levels: index, middle, ring, and little) and *Finger combination* (3 levels: IM, IMR, and IMRL) were selectively included in the analysis depending on the variable to be analyzed. Statistical significance (α) was set at 0.05. Furthermore, a paired *t*-test was used to verify the differences between the paired samples, and statistical significance (α) was set at 0.05.

3.3. Results

3.3.1. Finger force sharing pattern

The maximum force in each finger was measured to set the reference force for the main task. The maximum force was measured when all four fingers pressed the transducers simultaneously. The force produced by the index finger was greater than that produced by the remaining fingers, and no significant differences were found among the remaining three fingers. The force produced by the little finger tended to show large deviations across the participants in comparison with the size of the force per se. The results were confirmed by using one-way repeated measures ANOVA and paired *t*-test (Table 3-1).

In terms of the right and left (mediolateral) components (*x*-axis) of the force, participation of more fingers (increased kinematic DOF) tended to increase the right component (direction of the back of the pulling hand) of the resultant forces of the fingers (Figure 3-2a). Furthermore, the right component of the middle (M) and ring (R) finger forces tended to be greater than that of the index (I) finger force. These results were analyzed with two-way repeated measures ANOVA, including the finger-related factors (4 levels: I, M, R, and L) and finger combinations (3 levels: IM, IMR, and IMRL), which revealed that the main effects of the *Finger combination* and fingers were both statistically significant (*Finger combination*: $F_{[2, 14]} = 10.70$, $p < 0.005$, each *finger*: $F_{[3, 21]} = 5.32$, $p < 0.01$). The interaction effect of the *finger* and *Finger combination* was also significant ($F_{[6, 42]} = 4.03$, $p < 0.005$). This is presumed to be due to the trend that the forces produced by the index, middle, and ring fingers increased toward the right with an increasing number of fingers participating in the task while the force value for the little finger is 0 N in the IM and IMR conditions, but increases toward the left (palm of the pulling hand) in the IMRL condition. Furthermore, the paired *t*-test showed that M was > I and R ($p < 0.05$) in the IMR condition and M and R were > I and L ($p < 0.05$) in the IMRL condition.

In terms of the superior and inferior components (*y*-axis) of the force, the force

Table 3-1. Maximum force from each finger. The force value for each finger (index, middle, ring, and little) at the peak resultant force during a maximal voluntary contraction (MVC) task. Data for the eight participants are presented as means and standard deviations.

(Unit: N)

	Index	Middle	Ring	Little	$F_{[DOF]}$	*p*	*t*
Mean	29.75	16.46	11.09	14.93	$16.884_{[3, 21]}$	.000	I > MRL
SD	9.78	2.86	2.76	6.04			

produced by the index and middle fingers accounted for most of the force (Figure 3-2b). The upper (superior) component of the force increased with more fingers participating in the task; consequently, the resultant force shifted from a bottom-pulling form toward 0 N (reference force). These results were verified with two-way repeated-measures ANOVA, including the *Finger*-related factors and *Finger combinations*, which revealed that the main effects of the *Finger* and *Finger combinations* were both statistically significant (*Finger combination*: $F_{[2, 14]} = 15.14$, $p < 0.001$, each finger: $F_{[3, 21]} = 30.33$, $p < 0.001$). The interaction effect of the *finger* and *Finger combination* was also significant ($F_{[6, 42]} = 4.57$, $p < 0.005$), which is presumed to be a result of the trend that the force produced by the ring finger was 0 N in the IM condition, but the bottom (inferior) component of the force began to increase in the IMR condition. Furthermore, the paired *t*-test showed that IM was > IMR and IMRL for the index finger ($p < 0.05$), IM and IMR were > IMRL for the middle finger ($p < 0.05$), and IMR was > IMRL for the ring finger ($p < 0.05$).

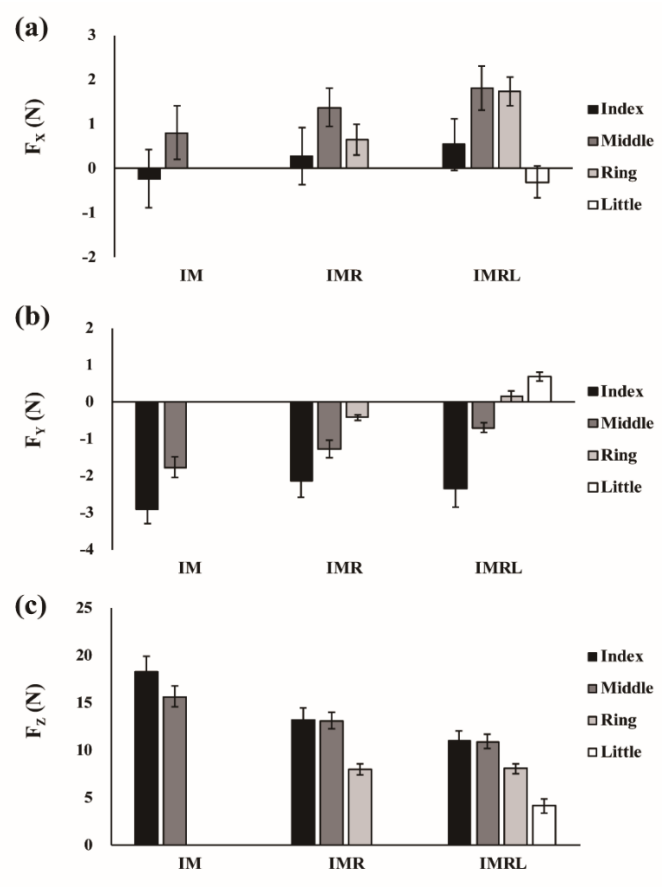

Figure 3-2. Force sharing pattern for each finger (index, middle, ring, and little) per finger combination (IM, IMR, and IMRL) in the aiming phase. The data for eight participants are presented as means and standard deviations. The *x*-axis (mediolateral; a: top), *y*-axis (superoinferior; b: middle), and *z*-axis components (anteroposterior; c: bottom) are shown

In terms of the anteroposterior component of the force (*z*-axis), participation of more fingers in the task tended to reduce the force produced by the index and middle fingers (Figure 3-2c). However, the difference between the index and middle finger forces tended to remain consistent irrespective of the number of fingers participating in the task. The ring and little fingers produced relatively smaller forces than the index and middle fingers Mi amorito (Kim, Uno 2013), and the ring finger produced a greater force than the little finger. These results were verified with two-

way repeated-measures ANOVA, including the finger-related factors and finger combinations, which revealed that the main effect of the *Finger combination* was not significant but that of the *finger* was significant ($F_{[3, 21]} = 77.45$, $p < 0.001$). The interaction effect of the *Finger* and *Finger combination* was significant ($F_{[6, 42]} = 60.75$, $p < 0.001$), which is presumed to result from the finding that the little and ring finger forces were equal to 0 N in the IM condition and the ring finger force was equal to 0 N in the IMR condition. Furthermore, the paired *t*-test showed that I, M>R sequence in the IMR condition ($p < 0.05$), and I, M, R>L sequence in the IMRL condition ($p < 0.05$).

3.3.2. Root mean square error

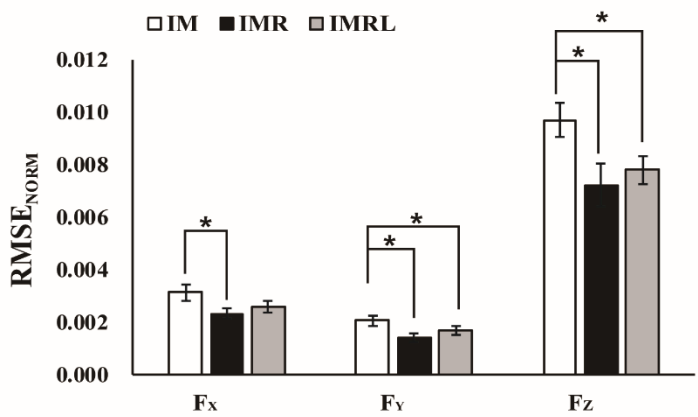

Figure 3-3. RMSE of the resultant forces for each finger combination (IM, IMR, and IMRL) and force component (*x*, *y*, and *z*-axes). The values were standardized on the basis of the target forces for each participant and averaged. The data for the eight participants are presented as means and standard deviations.

The RMSE for each axis component (mediolateral: *x*-axis, superoinferior: *y*-axis, and anteroposterior: *z*-axis) is presented according to finger combination condition (Figure 3-3). The RMSE values for all the components differed in relation

to the number of fingers participating in the task, and RMSE was relatively greater in the IM condition than in the other conditions. This was verified with one-way repeated measure ANOVA (x-axis: $F_{[2, 14]} = 4.789$, $p < 0.05$; y-axis: $F_{[2, 14]} = 5.293$, $p < 0.05$; z-axis: $F_{[2, 14]} = 12.520$, $p < 0.005$). The RMSE for each condition was compared with the paired t-test, which showed that IM > IMR sequence for the x-axis component ($p < 0.05$), IM > IMR, IMRL sequence for the y-axis component ($p < 0.05$), and IM > IMR, IMRL sequence for the z-axis component ($p < 0.05$).

3.3.3. Releasing time

The RT and standard deviations of RT in relation to the DOF of the fingers are presented in (Figure 3-4). One-way repeated-measures ANOVA and paired t-test revealed that no significant differences in RT in relation to *Finger combination* (Figure 3-4a) and among the standard deviations for the conditions (Figure 3-4b).

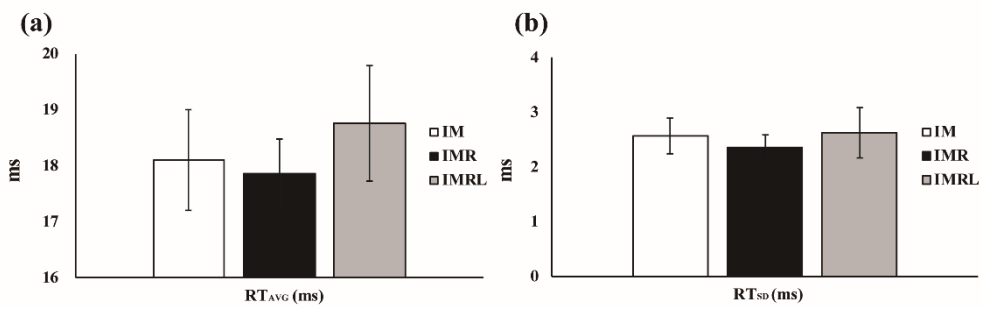

Figure 3-4. (a) Releasing time according to *Finger combination* (IM, IMR, and IMRL). (b) Standard deviation of the RT for each participant. The data for the eight participants are presented as means and standard deviations.

3.3.4. ACI and PRI

The ACI and PRI for the virtual projectile are presented for each finger combination (Figure 3-5). No significant change was found in ACI, which represents the accuracy of the firing with reference to the center of the target. On the other hand, the PRI, which represents the consistency across trials, significantly differed between the IM and IMR conditions, which was also verified by the paired *t*-test results (IM>IMR, $p < 0.05$).

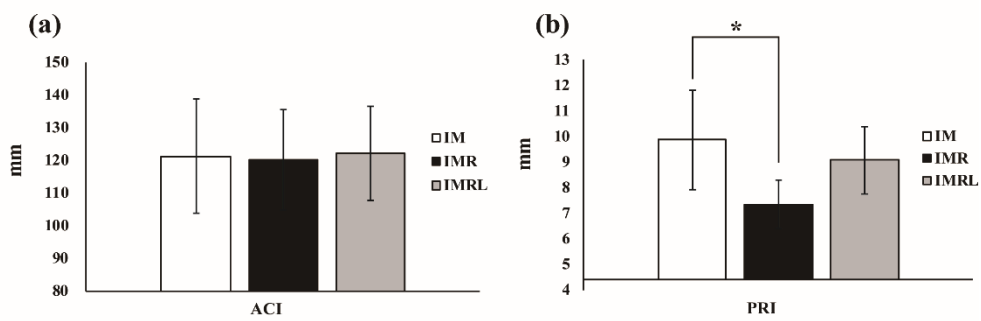

Figure 3-5. Accuracy index (ACI, a), the mean displacement of the location of the virtual projectile from the center of the virtual target for each finger combination (IM, IMR, and IMRL), and precision index (PRI, b), the mean distance of the location of the virtual projectile in a given trial from the mean location of the virtual projectile in previous trials. The data from the eight participants are presented as means and standard deviations.

3.4. Discussion

This study was aimed at investigating the effects of the DOF of the fingers on the performance of multi-goal tasks as follows: stabilization of force (static goal) and quick release of force (dynamic goal). The task used in this study emulates the

dynamics of aiming and releasing motions of the aiming and release motions in archery; hence, the findings of this study would provide valuable insights into understanding the kinetics and control of multi-digits in archery. Previous studies have reported that the most important determinant of archery performance is the finger movement in the release phase (Hah & Yi, 2008; Stuart & Atha, 1990). The DOF of the fingers may influence force control, which varies throughout the short release phase, viewing the relationship between the problem regarding the DOF of the fingers and the game performance from biomechanical and motor control perspectives would enable a broad understanding of successful shooting motion in archery. Previous studies have explained that using multiple fingers partially compensates the errors arising from each finger in some tasks (Latash et al., 1998; Latash et al., 2001; Scholz et al., 2002). Our findings show that the error of the resultant force of the fingers is reduced by increasing the number of fingers participating in the task. This suggests that increasing the kinetic DOF of the fingers reduces the error of the resultant force through an interaction among the forces produced by each finger, ultimately contributing to stabilizing the resultant force produced by the fingers.

Increasing the DOF more stably controlled the force in the aiming phase but did not improve the accuracy of the shooting (accuracy of the virtual projectile with reference to the center of the target) in the release phase. On the other hand, precision, which represents consistency across trials, was higher when three fingers were used than when two fingers were used. In addition to accurately shooting at the target, achieving consistent performance is a critical factor in superior archery performance (Leroyer et al., 1993; Martin, Siler, & Hoffman, 1990; Nishizono, Shibayama, Izuta, & Saito, 1987). Finger movement during a release motion in archery is achieved via

diverse strategies, including active contraction of the finger extensor and passive release by the bowstring by releasing the force of the finger flexors (Martin et al., 1990; McKinney & McKinney, 1990). A previous study reports that active extension of the finger during a release in archery hinders consistent shooting by displacing the lateral direction of the bowstring, suggesting that a passive form of release is more advantageous to achieving consistent scores (Martin et al., 1990). Furthermore, studies explain that extensive training is critical to attain this because a harmonious balance must be achieved between the relaxation of the finger flexors and contraction of the finger extensors (Ertan, Kentel, Tumer, & Korkusuz, 2003). According to our findings, increasing the DOF of the fingers is beneficial to consistent shooting in archery. To explain this phenomenon, we set equal reference forces across DOF conditions. In other words, increasing the DOF of the fingers may have reduced the load on each finger, and the relative reduction of force produced by each finger may have had positive effects on controlling the force of each finger.

Meanwhile, the ACI is directly related to RT. Increasing the RT increases the loss of energy stored in the bow throughout the release phase, which may be the culprit of missing the center of the virtual target. That is, the absolute length of the RT affects the ACI and deviations of the RT affects the PRI. The authors predicted that increasing the DOF of the fingers would increase RT, but RT did not significantly differ in relation to changes in the DOF of the fingers in the study. As previously explained, increasing the finger RT decreases the relative force produced and maintained by each finger, and it may be beneficial for releasing the force to 0 N. Such benefits might have offset the negative effects of increasing the DOF of the fingers. Meanwhile, no significant difference in RT deviation was observed across the conditions. This suggests that the improvement of precision as a result of

increasing the DOF of the fingers is not mediated by a consistent RT and that the stable control of the force throughout the aiming phase until right before the release would have been conducive to consistent performance of the task. In other words, consistent control of force as a result of an increase in DOF to a certain extent seems to bring about positive effects on task performance.

This study was conducted to test three hypotheses: first, increasing the DOF of the fingers will decrease the error of the resultant force of the fingers while, second, increasing RT, which, third, will not affect the outcome of task performance (accuracy and precision). The findings of this study support the first hypothesis but rejects the second and third hypotheses. The findings suggest that increasing the DOF of the fingers contributes to stabilizing the resultant force of the fingers and increases the precision of task performance.

The contribution of this study to understanding finger movements in multi-goal tasks is highly beneficial, considering the nature of archery, where precise performance across trials is critical. In an actual game, clickers are used to control the distance to which the string is drawn, and quick response to clickers is an essential skill demanded of archers (Leroyer et al., 1993). Furthermore, increasing the DOF of the fingers participating in the task also has negative aspects, as it hampers flexible response to the changes of such dynamic forces. In other words, increasing the DOF encompasses both positive and negative aspects. In studies to follow, we plan to substantiate the possibilities found in this study by examining additional variables, based on which we will investigate the optimal solution to multi-goal tasks, where positive factors are highlighted while negative factors are minimized.

The results of this study confirm the tendency of the smallest error and good

task performance in IMR condition. We could consider this to be a force magnitude defendant characteristic of the number of kinetic DOFs for task performance. One of the causative hypotheses is the contribution of little finger. In general, little fingers showed less contribution than other fingers, and additional analysis of this study showed that the coefficient of variation of little fingers was four times larger than the rest of fingers. The task of this study required to maintain the same reference force under all DOF conditions, and the force applied to each finger gradually decreased with increasing DOF. In other words, little finger participation is likely to be negative below a certain force value. This reduction in force is likely to be the cause of the tendency that the difference between the IMR condition and the IMRL condition is weakened or reversed compared to the difference between the IM condition and the IMR condition. However, further research will be needed to verify this possibility.

3.5. Conclusion

The decrease in the error of the resultant force suggests that the fingers employed in the task indeed compensate one another's errors, thereby stabilizing the performance variable, that is, the resultant force produced by the fingers. The findings of our study show that increasing the DOF of the fingers stabilized the resultant force of the fingers in the aiming phase through an interaction among the fingers and contributed to improving the precision of task performance.

Chapter 4. Effect of kinetic degrees of freedom on multi-finger synergies and task performance during force production and release task

Chapter 4 contains the following original paper reprinted by the permission from Springer Nature: **Kitae Kim**, Dayuan Xu, Jaebum Park (2018). Effect of Kinetic Degrees of Freedom on Multi-Finger Synergies and Task Performance during Force Production and Release Tasks. ***Scientific reports, 8***(1), 12758.

4.1. Introduction

The human body is a complex system of redundant forms in which the degrees-of-freedom (DOFs) of elements is generally larger than the DOFs (i.e., dimensionality) of task space, and this phenomenon has been postulated as the motor redundancy or the DOF problem (Bernstein, 1967; Latash, 2000). The redundancy emerges at various levels within the human movement system, and the redundancy theoretically enables the system to have numerous combinations of elements as solutions to an equivalent performance. The investigation on the strategies to govern a redundant set of elements in humans has been one of the most challenging issues, and no consensus has been made on the issue of the controller's strategy to solve the redundancy. From the engineering or mathematical point of view, the redundancy has been considered a negative aspect of the system due to a computational difficulty on the control system. Therefore, several studies have been conducted to formulate

computational models that examined an optimum solution by means of eliminating, freezing (Company et al., 2003), or coupling a redundant set of DOFs (Arimoto et al., 2003; Cheng & Orin, 1991; Xia et al., 2005). In the optimization of the redundant system, the existence of variability (or inconsistent combinations of elements) could reflect an erroneous neural process. An alternative idea suggests that the human controller utilizes redundant DOFs positively in such a way that the elements show purposeful covariations to satisfy a particular motor task resulting in forming a family of solutions as to portray flexible solutions. Also, the idea assumes that the variability within the family of solutions may be an indicator of the control process since there are task-related rules to form the family of solutions (Latash, 2008). Thus, specific performance could be executed successfully in a flexible manner while having a purposeful organization of elements. Indeed, experimental evidence has supported that the various combinations of elements equally satisfy a specific motor performance and the organization of flexible combinations of the elements depends on either mechanical necessities of the motor tasks (Karol et al., 2011; Latash et al., 2001) or choice of the controller for maintaining the stability of performance variables (Latash et al., 2001; Li et al., 1998; Scholz et al., 2002). Stability in traditional terms refers to the ability of the system to return to its original state in response to external perturbations (Ahn & Hogan, 2015). In the same context, the stability in the redundant system of human movements describes the ability to stabilize a specific performance variable by flexible sharing and error compensation among elements in task-specific manners (Park, Singh, et al., 2012; Singh, Varadhan, Zatsiorsky, & Latash, 2010).

The system of human hands and fingers has been modeled as a serial and parallel system, and the redundancy of the human hand system is observed through

both kinematic and kinetic variables. The previous studies regarding the solutions to the kinetic redundancy of the human hand system reported that individual finger forces co-vary to stabilize important performance variables that produces desired net mechanical outcomes such as net force or net moment (Latash et al., 2003; Latash et al., 1998; Latash et al., 2001; Latash et al., 2004; Park et al., 2011; Scholz et al., 2002). On the other hand, a recent study of finger force organization during pressing task quantified and compared optimal combinations and variability associated with finger forces, which showed that the optimal patterns of finger forces and their variance components are compatible (Park, Zatsiorsky, & Latash, 2010). During a multi-finger pressing task, covariation patterns for the net torque stabilization is in conflict with the covariation pattern for the force stabilization if only normal forces of two fingers were considered while the two finger forces produced opposite directional torques to each other (Latash et al., 2001). However, it is theoretically possible to stabilize both net force and moment simultaneously with the usage of more than two fingers, and a possible range of solutions relies on the number of redundant fingers involved in the task. Therefore, it may be advantageous to have a redundant set of fingers in producing and maintaining a certain amount of the net force and torque simultaneously with a more flexible pattern of finger force combinations. This expectation and experimental observation are in line with the concept of motor abundance (Gelfand & Latash, 1998; Latash, 2000). Hence, "Redundant" elements may not cause computational problem or errors of the neuronal process. Rather, the system with redundant elements could be viewed as a prerequisite for flexibility (or stability) upon a proper organization of finger actions. The strategies of organizing family of solutions for successful performance is definitely a process of neural structure in the biological system, and term, synergy,

has been proposed to describe and quantify the process and consequence of neural activities for governing a redundant set of finger forces. For the quantification of synergic actions of elements, the framework of the uncontrolled manifold (UCM) approach has been proposed (Scholz & Schoner, 1999; Scholz et al., 2000). The process includes selecting two lower dimensional subspaces within the space of elements. The first subspace is concerned with the manifold where the changes in the actions of elements have no net mechanical effect, and the second subspace is the orthogonal space to the UCM where the actions of elements do have net mechanical effect. If most of force variance of individual fingers is confined within the UCM, we may conclude that the net force is stabilized by the co-varied adjustment of individual finger forces.

Here, we would like to raise two follow-up questions regarding the organization of a redundant set of elements during multi-finger force production tasks. The first question is "How many kinetic DOFs of fingers would be best to stabilize net force and torque during multi-finger pressing task?" The second question is "Is the synergy beneficial to improve accuracy and precision of performance?" A shooting task could exemplify the topics raised by two questions, and the archery shooting with multiple combinations of fingers is a good candidate for motor tasks to examine the effect of kinetic DOFs and its further effect on the shooting performance. Apparently, successful shooting performance in the archery shooting depends on accurate and stable force production by multi-fingers during aiming, and quick release of the net finger force during force release to minimize the changes in momentum (Leroyer et al., 1993), which results in "good" shooting performance consistently. The terms, accuracy and precision, have been used to quantify the indices of the shooting performance (Leroyer et al., 1993; Martin et al., 1990; Nishizono et al., 1987). The

accuracy refers to the closeness of performed values to a required value, and the precision refers to the reproducibility of performances.

In the current study, we employed a multi-finger pressing task with a set of finger combinations (i.e., a set of DOFs of fingers) simulating the shooting motion of the archery. The main goal of the current study was to explore the effect of kinetic DOFs (i.e., number of involved fingers as force generators) on the stabilization of the total force and moment during stable force production. Further, we examined how the stability properties of multi-finger actions during a steady-state force production affect the shooting performance such as accuracy and precision. We tested the following hypotheses: (1) the synergy indices of both total force and moment will increase with the number of fingers during a steady-state force production, and (2) the accuracy and precision as the indices of shooting performance will increase (i.e., improved accuracy and precision) with the number of fingers.

4.2. Methods

4.2.1. Subjects

Eight right-handed young males (age 29.1±3.9 yrs, height 1.75±0.05 m, weight 72.8±8.7 kg) were recruited in the study. The handedness of all participants was right, which was determined by the Edinburgh inventory (Oldfield, 1971). None of the participants had a previous history of upper extremity injury including forearm, hand, and fingers. The research was conducted after signing the consent form approved by the Institutional Review Board (IRB) at Seoul National University (IRB No.

1703/002-006).

4.2.2. Equipment

A set of four 6-axis force transducers (Nano-17, ATI Industrial Automation, Garner, NC) was used to measure individual finger forces of all three axes. The transducers were attached to a vertically oriented aluminum frame (size: 90 × 140 × 250 mm). Finely round-shaped caps were inserted into the surface of the transducers, which allowed fingertips to have intentional roll or slide naturally. The distance between adjacent transducers was set at 2 cm along the *y*-axis (Figure 4-1), and the position of the panel with the transducers was adjusted along the *x*-axis according to the hand anatomy of individual subjects. Once the position of the panel was adjusted, the panel was mechanically fixed on the table throughout the whole experiment for each participant. The sampling rate of the force signals was set at 100 Hz. A 27-inch computer screen was positioned in front of the subject, which provided real-time force feedback.

4.2.3. Experimental Procedure

4.2.3.1. Maximal voluntary contraction (MVC) task

The participants were instructed to press on the transducers with all four fingers simultaneously as hard as possible until the maximum total finger pressing force (MVC_{TOT} about the *z*-axis) was achieved. Each trial was performed for 5 s, and the real-time visual feedback of total finger force (F_{TOT}) was provided on the screen. The maximal individual finger forces (MVC_i; i = {index, middle, ring, little}) were

captured at the time of MVC_{TOT}. The participants performed two consecutive trials, and the average MVC_{TOT} and MVC_i values across the two trials were used to set reference force levels for the next task.

4.2.3.2. Multi-finger force production and release (FPR) task

The participants were asked to produce a steady-state F_{TOT} with multiple fingers followed by a quick release of F_{TOT} in a self-paced manner. The task was a simulation of an archery shooting regarding the sequence of finger force changes (i.e., a steady-state force production for aiming followed by force release by taking off the fingers for shooting). The experimental conditions of the multi-finger combinations included 1) index-middle (IM), 2) index-middle-ring (IMR), and 3) index-middle-ring-little (IMRL). 10 s was given for each trial, which consisted of two phases: 1) steady-state force production and 2) force release phase. For the steady-state phase, it was instructed to maintain steady-state levels of force in both normal (*z*-axis) and tangential (*x*- and *y*-axis) directions within the first 5 s. The magnitude of the reference force (F_{REF}) of the *z*-axis was set at 50% of ΣMVC_i at corresponding condition (e.g., 50% of $\{MVC_I + MVC_M\}$ for the IM condition), while the F_{REF} of the *x*- and *y*-axis were set at zero (N).

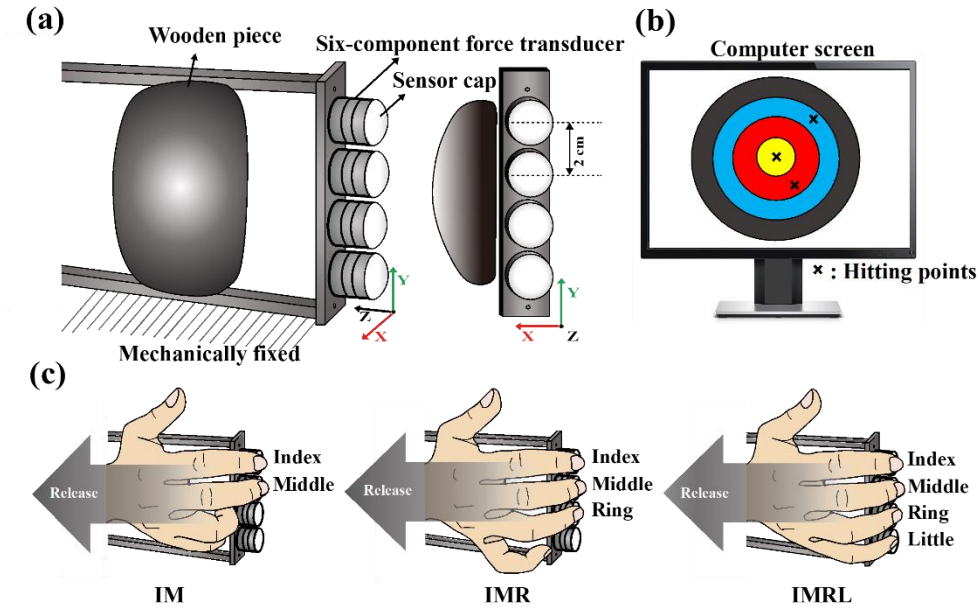

Figure 4-1. The experimental frame was mechanically fixed to the table and the sensors were attached to the experimental frame (size: 90 × 140 × 250 mm). The uncertainty values of the transducers as the validity of measurement were measured. The estimated results show the measurement errors ranged from 0.02 – 0.05 N for the force and 0.02 – 0.06 Ncm for the moment of force, which are compatible with the values reported in the previous studies. Finely round-shaped caps were inserted into the surface of the transducers, which allowed fingertips to have intentional roll or slide naturally. The distance between adjacent transducers was set at 2 cm along the *y*-axis, and a wooden piece was placed under the palm to ensure a consistent configuration of the hand and fingers during the tasks. The sampling rate of the force signals was set at 100 Hz. A 27-inch computer screen was positioned in front of the subject, which provided real-time force feedback. The refresh rate of the feedback screen was 60 Hz. (b) The computer screen displayed a hitting point of the virtual ball after the completion of a particular trial. The computer screen showed F_{TOT} produced by the participants and F_{REF}. After the completion of a particular trial, the computer screen showed a hitting point of the virtual ball by assuming that the trajectory of the ball was determined by the velocity at the moment of release and gravitational force (g = 9.81 m/s^2) acting on the ball. (c) Hand and finger configurations for three experimental conditions. The thumb was parallel to the fingers and naturally flexed the proximal interphalangeal joint to 10 - 20º. Similarly, non-involved fingers in the IM and IMR conditions were also flexed naturally while not contacting transducers; therefore, the thumb and non-involved finger (s) had no mechanical effect on the frame during the task.

For the force release, the participants were instructed to release finger forces as quickly and smoothly as possible within the next 5 s by translating the forearm and hand toward the trunk. The instruction of "*quick*" and "*smooth*" release was for minimizing the release time (i.e., minimum changes in momentum). The computer screen showed F_{TOT} produced by the participants and F_{REF}. After the completion of a particular trial, the computer screen showed a hitting point of the virtual ball by assuming that the trajectory of the ball was determined by the velocity at the moment of release and gravitational force ($g = 9.81$ m/s^2) acting on the ball (Figure 4-1). The initial velocity was computed by Equation 3-1 (Chapter 3). The horizontal distance from the release point to the virtual target was set at 0.7 (m/N) × ΣMVC_i. Prior to the data collection, the participants performed practice trials for about 30-40 min. For the data collection, the participants performed consecutive 25 trials for each condition. 10 s break between every two trials and more than 5 min break between the conditions were provided.

4.2.4. Data analysis

Customized codes were written to analyze the finger force data. Before variable computation, a digital zero-lag 4th-order low-pass Butterworth filter with a cutoff frequency of 10 Hz was applied to the raw force data. In addition, following indices of timing variable were detected within a single trial. The t_0 was defined as the time moment when the first derivative of F_{TOT} (dF/dt) reached 5% of the first negative peak of dF/dt. The duration of the steady-state phase was defined as between -1500 ms and -500 ms prior to t_0. The time of completion of force release (t_1) was defined as the time moment when F_{TOT} reached 0 N after t_0.

4.2.4.1. Performance indices

$RMSE_{NORM}$: Root mean squared error (RMSE) was computed using Equation 3-2 (Chapter 3). during the steady-state phase.

Release time (RT): RT was defined as time duration between t_0 and t_1. Further, we quantified average (RT_{AVG}) and standard deviation (RT_{SD}) of RTs across repetitive trials in each participant and condition.

Accuracy (ACI_{NORM}) and precision index (PRI_{NORM}): The accuracy index (ACI) was quantified as an average Euclidean distance between the hitting position of the virtual ball and the center of the virtual target across repetitive trials using Equation 3-3 (Chapter 3). The precision index (PRI) was quantified as an average Euclidian distance between the hitting position of the virtual ball and mean hitting position across repetitive trials using Equation 3-4 (Chapter 3). The ACI and PRI were further normalized by the reference force (F_{REF}).

4.2.4.2. Multi-finger synergy indices

The framework of uncontrolled manifold (UCM) approach was employed to quantify the synergy indices of stabilizing two sets of performance variables, resultant force (F_{TOT}) of three axes and the moment of force (M_{TOT}) about the *x*- and *z*-axes, separately. The repetitive trial data were aligned with respect to t_0. The elemental variables in the current analysis were finger forces, and the performance variables included F_{TOT} and M_{TOT}. For the moment of force computation, we assumed that the center of rotation was located at the mid-point between two lateral fingers on the level of the surface of the sensors along the *y*-axis, and moment arms of individual finger forces were fixed.

The change in elemental variables (*d*EV) sum up to produce changes in the performance variables (*d*PV). The EVs in the current analysis included finger force vector, and the PVs were F_{TOT}.

$$dPV = J \cdot dEV \qquad \text{(Equation 4-1)}$$

, where, J represent 1 by n Jacobian matrix, and n is the number of degrees-of-freedom of the EVs in the task. The UCM was defined as a unit vector (e_i) in the space of elemental variable that did not change the given performance variables (PV).

$$0 = J \cdot e_i \qquad \text{(Equation 4-2)}$$

. The manifold was found by computing the null space of the Jacobian of this transformation (i.e., linearly approximated null space spanned by the basis vector). The mean-free EVs were then projected onto the manifold and summed to produce

$$f_{\parallel} = \sum_{i}^{n-p} (e_i^T \cdot \mathrm{d}f) e_i \qquad \text{(Equation 4-3)}$$

, where, p is the number of DOFs of the performance variable. The component of the demeaned EVs orthogonal to the null-space is given by

$$f_{\perp} = df - f_{\parallel} \qquad \text{(Equation 4-4)}$$

. The amount of variance per degree of freedom parallel to the UCM is

$$V_{UCM} = \frac{\sum |f_{||}|^2}{(n-p)N_{trials}} \qquad \text{(Equation 4-5)}$$

. The amount of variance per degree of freedom orthogonal to the UCM is

$$V_{ORT} = \frac{\sum |f_{\perp}|^2}{pN_{trials}} \qquad \text{(Equation 4-6)}$$

. The time function of synergy index, ΔV(*t*), was further computed using Equation 4-7 (see Latash et al. 2003 for computational details). Note that the variances in Equation 4-7 were normalized by the DOFs of the corresponding subspace.

$$\Delta V(t) = \frac{V_{UCM}(t) - V_{ORT}(t)}{V_{TOT}(t)} \qquad \text{(Equation 4-7)}$$

. Further, the ΔVs were log-transformed using the Fischer transformation applied for the computational boundaries (i.e., -2 to +2 for the IM, from -3 to +1.5 for the IMR, from -4 to +1.33 for the IMRL condition).

4.2.5. Statistical analysis

The data are presented as means and standard error. Repeated measured

ANOVAs with factors *Finger* (four levels: index, middle, ring and little), *Axis* (three levels: *x*-, *y*-, and *z*-axis), *Finger DOF* (three levels: IM, IMR, IMRL), and *Variance* (two levels: UCM and ORT) were used. Notably, we explored how the main outcome variables ($RMSE_{NORM}$, RT_{AVG}, RT_{SD}, ACI, PRI, ΔV_F, ΔV_M) were affected by the factors. The factors were selected based on particular statistical tests. For the repetitive measures of the force values of three axes (F_X, F_Y, F_Z), the intra-class correlation coefficents (ICC) as an index of test-retest reliability were estimated for IM condition (ICC = .954 for F_X, $p < .001$; ICC = .977 for F_Y, $p < .001$; ICC = .997 for F_Z, $p < .001$), IMR condition (ICC = .927 for F_X, $p < .001$; ICC = .986 for F_Y, $p < .001$; ICC = .999 for F_Z, $p < .001$), and IMRL condition (ICC = .981 for F_X, $p < .001$; ICC = .969 for F_Y, $p < .001$; ICC = .996 for F_Z, $p < .001$). Mauchly's sphericity test was used to confirm the assumptions of sphericity, and the Greenhouse-Geisser correction was used when the sphericity assumption was rejected. For the post-hoc test, multiple pairwise comparisons with Bonferroni correction was conducted. Linear regression analysis was used to examine the relations between the synergy indices (ΔV_F) and performance indices (ACI and PRI). All statistical significance level was set at $p < 0.05$.

4.3. Results

The motor task in the current study imitated the finger actions of the archery in such a way that the participant produced a steady-state value of finger force followed by the release of the force quickly. In addition, the participants performed the tasks with a set of finger combinations that was incorporated with the kinetic DOFs of actively involved fingers during the tasks. Shooting performance was

quantified by the indices of accuracy and precision, which refers to the distance to the target value and the reproducibility of repetitive attempts, respectively. The framework of uncontrolled manifold analysis was used to quantify force variance within two subspaces of finger forces and the synergy indices as a stability property of net force and moment production. Further, we examined correlations between the indices of task performance and multi-finger synergy indices. See the Methods section for more details.

4.3.1. Performance indices

4.3.1.1. $RMSE_{NORM}$

The root mean squared error normalized by reference force ($RMSE_{NORM}$) during a steady-state force production was relatively larger in the *z*-axis (i.e., the axis of normal force) compared to the $RMSE_{NORM}$ of the other two axes. In addition, the $RMSE_{NORM}$ decreased with the number of fingers (DOFs) in the *y*-axis (superior-inferior) and *z*-axis. The $RMSE_{NORM}$ of the *x*-axis (medial-lateral) was similar between the conditions (Figure 4-2). A two-way repeated measure ANOVA supported these findings with factors *Axis* (three levels: x-, y-, and z-axis) and *Finger DOF* (three levels: IM, IMR, and IMRL), which showed significant main effects of *Axis* ($F_{[0.08,7.57]} = 77.97$, $p < 0.001$, $\eta p^2 = 0.92$) and *Finger DOF* ($F_{[2,14]} = 5.65$, $p = 0.02$, $\eta p^2 = 0.54$) with a significant *Axis* × *Finger DOF* ($F_{[1.80,12.58]} = 8.70$, $p < 0.001$, $\eta p^2 = 0.55$). A significant factor interaction reflected the fact that a significant effect of *Finger DOF* was observed only in the *y*- and *z*-axis. Pairwise comparison confirmed that the $RMSE_{NORM}$ of IM > IMR, IMRL for the *y*-axis ($p < 0.05$) and IM, IMR > IMRL for the *z*-axis ($p < 0.05$).

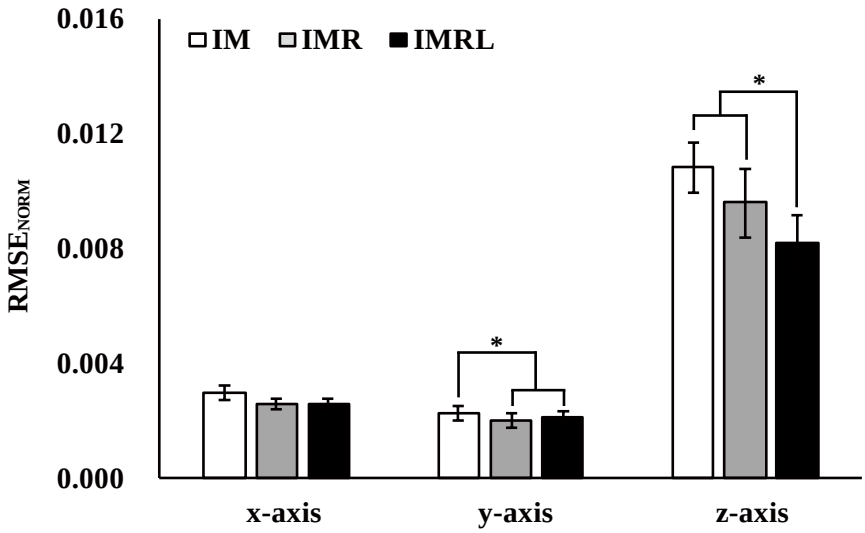

Figure 4-2. $RMSE_{NORM}$ at the steady-state force production for the *x*-, *y*-, and *z*-axis are presented for the IM (white bars), IMR (gray bars), and IMRL conditions (black bars). Values are means ± standard errors across subjects. The asterisks show significant differences in pairwise comparisons between the conditions ($p < 0.05$).

4.3.1.2. Release time (RT)

The participants performed 25 repetitive trials for the multi-finger force production and release (FPR) task for each DOF condition. Generally, there was no significant difference in the average release time across the trials (RT_{AVG}) between the conditions. However, the standard deviation of RT (RT_{SD}) decreased with the number of fingers. In other words, the RT was more consistent when the number of involved fingers was increased. A one-way repeated measure ANOVA with factor *Finger DOF* (three levels: IM, IMR, and IMRL) on RT_{SD} supported these findings ($F_{[2, 14]} = 5.42$, $p = 0.02$, $\eta p^2 = 0.44$). Post-hoc pairwise comparisons confirmed RT_{SD} of IM, IMR > RT_{SD} of IMRL ($p < 0.05$).

4.3.1.3. Accuracy index (ACI_{NORM}) and precision index (PRI_{NORM})

The indices of accuracy (ACI_{NORM}) and precision (PRI_{NORM}) decreased together with the number of finger DOFs (i.e., the larger the number of fingers for the task, the better accuracy and precision for the performance). These findings were supported by one-way repeated measure ANOVAs with factor *Finger DOF* (three levels: IM, IMR, and IMRL) separately on ACI ($F_{[1.10, 7.72]} = 57.53$, $p < 0.001$, $\eta p^2 = 0.89$) and PRI ($F_{[2, 14]} = 29.73$, $p < 0.001$, $\eta p^2 = 0.81$). Post-hoc pairwise comparisons confirmed that IM > IMR and IMRL for ACI ($p < 0.05$), and IM > IMR > IMRL for PRI ($p < 0.05$).

4.3.2. Multi-finger synergy indices

4.3.2.1. Force stabilization hypothesis

First, we compared mean differences of each component of variances per DOF for the force stabilization hypothesis (V_{UCM}^F and V_{ORT}^F) between the conditions and axes. The variances were normalized by the square of the relevant reference force (F_{REF}) about the *z*-axis. In general, both V_{UCM}^F and V_{ORT}^F decreased with the number of finger DOFs for all three axes. In particular, V_{UCM}^F was smaller than V_{ORT}^F in the *x*-axis, while V_{UCM}^F was larger than V_{ORT}^F in the *z*-axis (axis of normal force) (Figure 4-3). Two-way repeated measure ANOVAs with factors *Finger DOF* (three levels: IM, IMR, and IMRL) and *Variance* (two levels: UCM and ORT) was performed separately on the variances of each axis. The results showed significant main effects of *Finger DOF* (*x*-axis: $F_{[2, 14]} = 7.66$, $p = 0.01$, $\eta p^2 = 0.52$; *y*-axis: $F_{[1.16, 8.11]} = 5.13$, $p = 0.05$, $\eta p^2 = 0.42$; *z*-axis: $F_{[2, 14]} = 6.53$, $p = 0.01$, $\eta p^2 = 0.48$) and

Variance (x-axis: $F_{[1, 7]} = 9.52$, $p = 0.02$, $\eta p^2 = 0.58$; z-axis: $F_{[1, 7]} = 6.53$, $p < 0.01$, $\eta p^2 = 0.78$) without factor interactions.

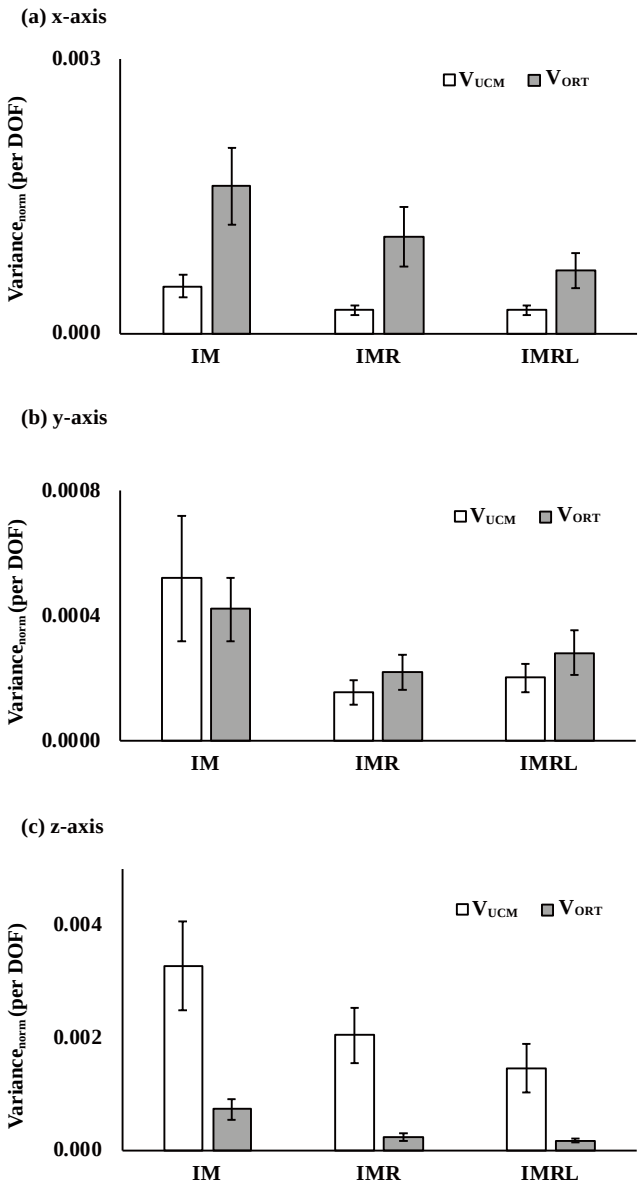

Figure 4-3. Two component of variances related to F_{TOT} stabilization, V_{UCM} (white bars) and V_{ORT} (gray bars) per degree-of-freedom, in the finger force space are presented for (a) x-axis, (b) y-axis, and (c) z-axis. Values are means ± standard errors across subjects.

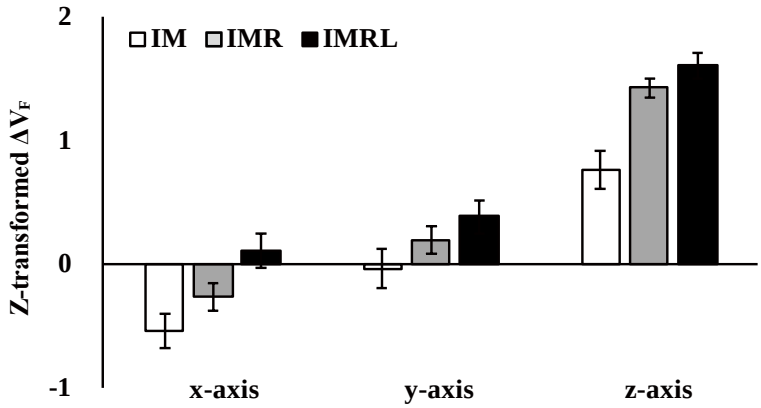

Figure 4-4. Z-transformed synergy indices with respect to F_{TOT} stabilization, ΔV_F, for the IM (white bars), IMR (gray bars), and IMRL conditions (black bars) at the *x*-, *y*-, and *z*-axes. Values are means ± standard errors across the subjects.

Further, we quantified the indices of synergies for the force stabilization (ΔV_F) during the steady-state force production. Overall, ΔV_F increased with the number of finger DOFs for all three axes, and the stabilization of normal force (ΔV_F^Z) was stronger than the stabilization of tangential forces (ΔV_F^X and ΔV_F^Y) (Figure 4-4). These findings were supported by a two-way repeated measure ANOVA on ΔV_F setting factors as *Finger DOF* (three levels: IM, IMR, and IMRL) and *Axis* (three levels: *x-, y-,* and *z*-axis). The results showed significant main effects of *Finger DOF* ($F_{[1.21, 8.49]} = 40.23$, $p < 0.001$, $\eta p^2 = 0.85$) and *Axis* ($F_{[2, 14]} = 74.89$, $p < 0.001$, $\eta p^2 = 0.92$) without factor interactions. Post-hoc pairwise comparison confirmed ΔV_F of IM < IMR < IMRL ($p < 0.05$), and ΔV_F of *x*-axis < *y*-axis < *z*-axis ($p < 0.05$).

4.3.2.2. Moment stabilization hypothesis

We computed the synergy indices of the moment of force about the *x*- (ΔV_M^X) & *z*-axis (ΔV_M^Z) with the assumption of fixed moment arms for individual fingers. Note that the moment of force about the *y*-axis was zero due to the zero moment arm

about the *x*- & *y*-axis. During the steady-state force production, ΔV_M increased with the number of fingers as the results of ΔV_F showed. In particular, the average ΔV_M^X across the participants was negative in the IM condition, while it became positive in the IMRL condition (Figure 4-5). ΔV_M^Z was positive for all DOF conditions. A two-way repeated measure ANOVA on ΔV_M with factor *Finger DOF* (3 levels: IM, IMR, and IMRL) and *Axis* (three levels: *x*-, and *z*-axis) confirmed a significant main effect of *Finger DOF* ($F_{[2, 14]} = 14.25$, $p < 0.001$, $\eta p^2 = 0.67$) and *Axis* ($F_{[1, 7]} = 91.28$, $p < 0.001$, $\eta p^2 = 0.93$) with factor interactions ($F_{[2, 14]} = 24.98$, $p < 0.001$, $\eta p^2 = 0.78$). Post-hoc pairwise comparison confirmed ΔV_M^X of IM < IMR < IMRL ($p < 0.05$) and ΔV_M^Z of IM, IMRL < IMR ($p < 0.05$).

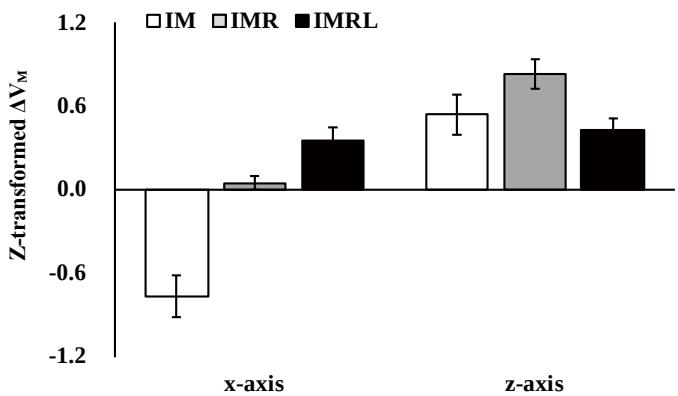

Figure 4-5. Z-transformed synergy indices related to M_{TOT} stabilization, ΔV_M, for the IM (white bars), IMR (gray bars), and IMRL conditions (black bars) at the *x*-axis. Values are means ± standard errors across the subjects.

4.3.3. The comparison between synergy indices and performances indices

Figure 4-6 illustrates the findings for the sets of synergy indices (e.g., ΔV_F^X, ΔV_F^Y, and ΔV_F^Z) and the variables associated with the performance indices (e.g.,

ACI and PRI) across all individual subjects and conditions. For most cases, there were significant negative correlations between the synergy indices and performance variables (e.g., ACI and PRI) across subjects and conditions (i.e., the larger synergy indices, the better accuracy and precision). In particular, the coefficient of correlation (r) was larger in ΔV_F^Z vs. both ACI and PRI than in the synergy indices of the other axes vs. the performance indices (ΔV_F^Z: r = -0.63 for ACI, r = -0.72 for PRI; ΔV_F^X: r = -0.47 for ACI, r = -0.39 for PRI; ΔV_F^Y: r = -0.35 for ACI, r = 0.06 for PRI, $p < 0.05$ for all comparisons except ΔV_F^Y vs. PRI). Further, the three large points in Figure 4-6 present the overall mean values of the synergy and performance indices across the subjects within each experimental condition (e.g., IM, IMR, or IMRL).

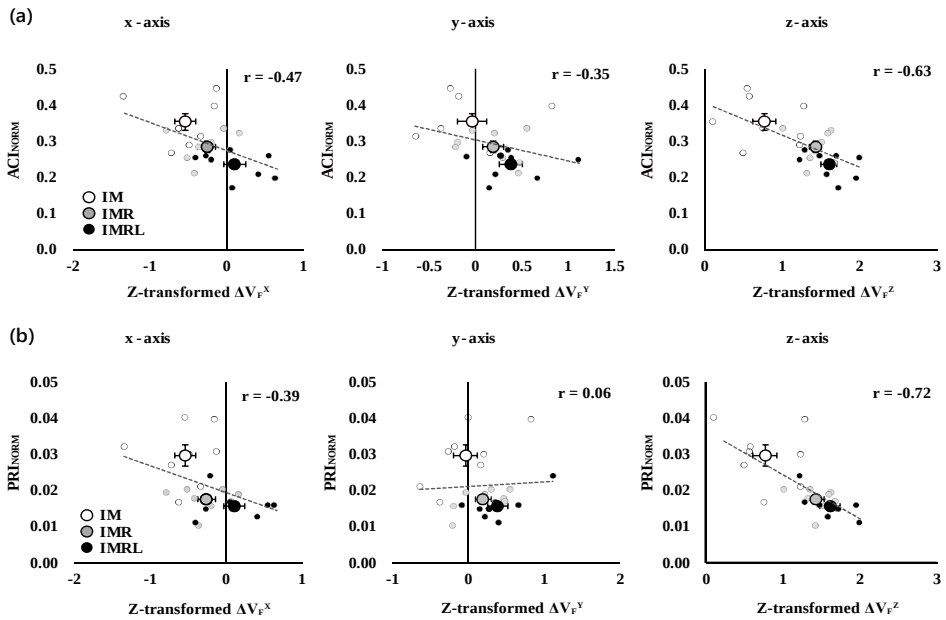

Figure 4-6. Correlation between the synergy indices of F_{TOT} stabilization for three axes (i.e., ΔV_F^X, ΔV_F^Y, and ΔV_F^Z) and (a) accuracy index (ACI) and (b) precision index (PRI). Small dots represent individual subject data for the IM (white), IMR (gray), and IMRL (black) conditions. The regression lines are shown with the coefficient of determination (r-value). The average values across subjects for the IM (white), IMR (gray), and IMRL (black) condition are presented with standard error bars in large circles.

The mean values were aligned along negative straight lines in most cases. These results reflect that the increase in synergy indices with larger DOFs of fingers was closely related to the increase in accuracy and precision of the performance (i.e., decrease in ACI and PRI).

4.4. Discussion

The main goal of the current study was to explore the effect of kinetic DOFs as finger force generators on the force and moment stabilization synergies and simulated shooting performances. The motor task given in the study imitated finger actions of the archery-shooting that the participants produced a steady level of isometric finger force followed by the release of net finger force. In addition, the participants performed the tasks with a set of finger combinations that was incorporated with the kinetic DOFs of elements. "*Good*" shooting performance was quantified by the indices of accuracy and precision, which refers to the closeness of performance to the target value and the reproducibility of repetitive attempts, respectively. The framework of uncontrolled manifold analysis was used to quantify force variances within two subspaces of finger forces and the synergy indices as a stability property of net force and moment production. We tested two hypotheses formulated in the Introduction, and all leading hypotheses have been confirmed. The strength of synergy indices for both net force and moment increased with the number of fingers during the steady-state force production. Also, the accuracy and precision as the indices of shooting performance improved with the number of fingers. Further,

the results showed that the indices of shooting performance were significantly correlated with the strength of stability properties (i.e., synergy indices) of both force and moment stabilization and their changes with the kinetic DOFs.

According to the principle of motor abundance (Gelfand & Latash, 1998; Latash, 2000), flexible combinations of finger forces within a redundant set of elements to the task mechanics could be interpreted as the strategies employed by the controller since the organization of force variability is not uniform for every task. Preferably, the patterns of variability (i.e., covariation) of elements comply with a set of rules considering at least mechanical necessities of the task. Indeed, the relatively large across-trial variance is generally observed in the subspace where equal performance (i.e., mechanical necessity) is achieved compared to the variance observed in the orthogonal space to it. Thus, the idea that the variability as a neuromotor noise (Harris & Wolpert, 1998) may not be fully supported. Instead, the underlying mechanism of the organization of variability may include purposeful flexibility to satisfy the task performance and to minimize the performance error, which is well fit with the idea of stochastic optimal control model (Todorov & Jordan, 2002). The results of current study showed that the redundant set of fingers affects positive changes in the net force error to the target value by showing that the net force error (e.g., $RMSE_{NORM}$) and error variance (V_{ORT}) were the smallest when all four fingers were involved La unica (Kim, S. 1982). The small error observed in the four fingers should positively affect the accuracy and precision of the performance as the experiment was designed. The rules mentioned above describe the flexible sharing and covariation between redundant elements for error compensation resulting in the stabilization of salient performance variable (e.g., net finger force). Here, we would like to emphasize that the flexibility is not a prerequisite for the

smaller performance error. This means that the consistent combinations of finger forces could also be the solution for small performance error, which is assumed to be a unique optimal solution. Thus, we can say that the net force error in the current results could be combined with flexible combinations of finger forces for the purpose of error compensation among active elements. Now, we come back to the questions of "How many kinetic DOFs of fingers would be the best to stabilize net force and torque during multi-finger force production task?" We know the fact that the ring and little fingers are relatively weak and less independent in their force production (Zatsiorsky et al., 2000) as well as the motion of joints (Li, Dun, Harkness, & Brininger, 2004). Also, the damping ratio of the two fingers, which assumes to be indicative of stability, is smaller than that of the other two fingers (Park, Pazin, Friedman, Zatsiorsky, & Latash, 2014). So, one may think that the use of those two fingers is not helpful to improve performance and stability. However, the experimental evidence is opposite to the expectation. The previous and current results showed that the involvement of those two fingers was not detrimental, but somewhat beneficial to the overall performance and stabilization of the performance. These outcomes could also be associated with the results of a recent study about the effect of fatigue, which showed that the interaction of individual effectors reduces the error caused by the fatigued element (Park, Singh, et al., 2012; Singh et al., 2010). This can be evidence that the controller is actively using redundant DOFs of multi-elements by minimizing performance error. In the same context, the large value of the multi-finger synergy index was observed in the condition that the number of fingers was large (Karol et al., 2011). The results demonstrate that a condition with a large number of finger DOFs may be more advantageous for stabilizing a given performance variable.

The explicit external constraint in the current experiment was to produce equal net finger forces to reference forces in all three axes, and the net moment of forces was not mechanically constrained. The results showed that both net pressing force and corresponding moment of pressing force were stabilized especially when all four fingers were explicitly involved. Particularly, relatively strong stabilization of net force was observed compared to the stabilization of moment of force. If a set of the mechanical constraints in motor task was to satisfy both net force and moment of force constraints simultaneously, and only normal components of finger forces were considered with fixed fingertip contacts, two subspaces spanned by the eigenvectors of the Jacobians of the two motor tasks are orthogonal to each other. The intersection between the two subspaces confines the solutions of finger forces for satisfying the mechanics of net force and moment. With the case of two normal finger forces with two task constraints, a unique combination for finger forces satisfying the two tasks (i.e., optimal combination) could be set since the intersection between the two subspaces is not space, but a point, so that the redundancy is disappeared. If the system is redundant, however, the intersection forms space, and the dimensionality of the intersection space (i.e., solution space) depends on the number of redundant DOFs. This implies that the variability of finger force combinations is feasible observation, which satisfies the two constraints. By combining this knowledge with the current results, it is possible that the additional constraints (or satisfaction) about the moment stabilization may be embedded in the hand action and its control when the system has relatively large redundancy. Indeed, it is well discovered that the apparent task mechanics (e.g., net force production task) does not exclusively define actual variables to be stabilized selectively (Karol et al., 2011; Latash et al., 2007). Maybe, the variables actually being controlled are not

cognitively recognized, but are the part of the controller's consideration to stabilize something else. It has been reported that both total force and moment of force could be stabilized with sufficient active elements in multi-digit pressing and grasping tasks (Shim, Latash, et al., 2005; Shim, Olafsdottir, et al., 2005; Shim et al., 2006). Further, the force and the moment were stabilized together even when moments are not provided as feedback (Karol et al., 2011; Latash et al., 2007).

The elemental variables in the current analysis were the finger forces, and it is well known that the production of four finger forces is interdependent due to the phenomenon of enslaving (i.e., unintended force production or motion by non-task digit). The finger force enslaving is caused by two groups of factors that include the mechanical coupling of finger actions by passive connection and the overlapped representation of the digits in the hand area within the primary motor cortex. Due to these factors of the enslaving, the structure of observed variances of mechanical variables (e.g., finger forces) may not definitely reflect the particular control strategy for a specific task. Instead of using interdependent mechanical variables, the variables that reflect the scheme of the controller have been introduced, and the variables are termed as force modes (Latash et al., 2003) for more details about force mode). A set of the elemental variables employed in the current analysis was finger forces in both normal and shear directions. It has been shown that the enslaving patterns of tangent directional forces are not as simple as those of normal forces, and particular relations between the interdependency of normal and tangential forces has not been discovered yet. So, we focused on the variability and its effect on the performance using a set of mechanical variables, finger forces in the current study. Nevertheless, we have to admit that the current results of the positive index of the moment stabilization cannot fully be viewed as a purposeful organization by the

controller.

Then, what are the benefits of additional constraints such as the moment stabilization into motor tasks? One obvious observation in the current result was that the accuracy and reproducibility of the performance were enhanced when all four fingers were involved, and it seems that the additional moment of force constraint was activated only with the use of all four fingers. Again, the moment of force was not dramatically stabilized when two or three fingers (e.g., IM and IMR conditions) were involved. Theoretically, net moment of force had no effect on the accuracy and precision as the algorithms for the hitting point was programmed in the current study. Theoretical solution space of force-moment task is smaller than space spanned by the Jacobian of one of them. Indeed, the results show that the two variances per dimension, V_{UCM} and V_{ORT}, decreased together with the number of fingers, while the synergy indices increased. In the computational point of view, the synergy indices refer to the relative magnitudes of V_{UCM} to V_{ORT} with respect to the total variance (V_{TOT}) across multi-attempts. This means that the strength of stability properties (i.e., synergy index) does not depend on the magnitudes of the two variances separately, but on their relative magnitudes. In other words, less flexible combinations of elements (i.e., smaller variances) could be associated with better stability. We know that a unique optimal solution describes a preferred pattern of sharing between the redundant elements. Therefore, less flexible patterns of finger force combinations in the current result may be inclined to the optimal combination of finger forces in case that it minimizes a specific cost function. Thus, it is probable that the finger force combinations are closed to optimal combination without an expense of stability given the condition that more fingers are actively involved in the motor task. Rather, redundant degrees-of-freedom may be a prerequisite to stabilize the given (i.e., net

force) and selected (i.e., net moment of force) performance variables with more converged solutions. Then, what is the nature of cost-function in the current experiment and data set? We do not have the relevant result to answer this question at the moment, and the answer will not be trivial and straightforward. Based on the current results of increased stability index with smaller variance at four finger case, however, we infer that the cost to be minimized may not be energy consumption since it has been mathematically and experimentally proved that the system could not reproduce robust stability during conservation of energy (Ahn & Hogan, 2012). This speculation is also an important part of a more general movement such as gait since robust stability takes higher priority over energy consumption (Ahn & Hogan, 2012). In case of sports such as archery, improvement in accuracy and precision of performance is only possible with stabilization of force. From our results, it is also evident that accuracy and precision is increased with the number of active fingers (i.e., increase in DOFs). Hence, stability takes a higher priority than energy consumption in case of sporting events more than that of a conventional movement used in everyday life. Thus, there may be a trade-off between minimization of energy consumption and stable performance (i.e., extra energy is necessary to resist and maintain stability).

4.5. Conclusion

It seems that the idea of motor abundance is well supported by the fact that the synergy indices increased with the number of fingers during steady-state force production. Notably, the elimination of redundant degrees-of-freedom was not

observed, but explicitly involved fingers were all contributed to maintaining stability of the important mechanical variables. Also, the enhanced synergy strength (i.e., magnitude of synergy indices) were highly correlated with the indices of shooting performance. The advantage of having an abundant set of elements supports the models of back-coupling feedback loops that describes two separate control processes for defining preferred and flexible sharing patterns (Latash et al., 2005). Based on the model and a few current results (Park, Singh, et al., 2012; Park et al., 2010), the optimality and variability may be complimentary ideas in a redundant (abundant) human motor system. In summary, changes in synergy observed from the current and previous data, the validity of the classical theory of freezing or freeing of degrees-of-freedom comes into question. Henceforth, instead of selectively utilizing degrees-of-freedom, all of it is used systematically. However, depending on the "abundant" set of degrees-of-freedom, patterns and strength of their covariation may change with respect to the nature of the performance variable.

Chapter 5. Effect of kinetic degrees of freedom on hierarchical synergies during force production and release task

5.1. Introduction

The human body system has a specific characteristic of motor redundancy. It is caused by the fact that the elemental variable involved in achieving the goal has a relatively large degree of freedom as compared to the performance variable. Thus, various combinations are possible for the human motor control system to perform a certain task. Such motor redundancy, in other words, how the central nervous system (CNS) effectively controls a large number of degrees of freedom of the human body is one of the major issues of concern in human movement science, and many studies have been conducted from various perspectives. Looking at the motor redundancy from an engineering point of view, an increase in redundant degrees of freedom can be seen as a burden on the controller. Therefore, research to find the only solution that optimizes the factors considered most importantly by the controller among various solutions is a very reasonable approach, and various researches are being conducted not only in mechanical aspects (Arimoto et al. 2003; Cheng & Orin, 1991; Xia et al. 2005) but also in human movement science (Li, Tart, Fitzsimmons, Storm, Mao, & Rolfes, 1991; Albrecht, Leibold, & Ulbrich, 2012). However, previous studies that have projected motor redundancy into human motion in terms of

variability reported that these redundant degrees of freedom interact with each other to stabilize key performance variables (Gelfand, & Tsetlin, 1966; Li et al. 1998, Latash, Scholz et al. 2001, Scholz, Danion et al. 2002; Park, Jo et al. 2013). In other words, the various types of movements enabled by motor redundancy are the result of the interaction of each element to complete the task. From the point of view of the human movement control by the central nervous system, the variability itself created by the combination of each elemental variables can be understood positively (Latash, Danion et al. 2003).

On the other hand, recent previous studies have shown that increasing the redundant kinetic degrees of freedom in the human body does not simply increase the variability of the solution. Rather, the inclusion of intrinsic constraints that are not cognitively given as tasks can be advantageous in stabilizing given performance variables with near optimal solutions. In other words, optimality and flexibility are not contradictory concepts, but less flexible combinations of elements (i.e., smaller variances) could be associated with better stability (Kim et al. 2018). In the previous study, we observed a change in the stability index (Synergy index) in which each finger force stabilizes the total force and moment as the number of finger degrees of freedom increases through an experimental method that reproduces the aiming and release behavior of archery. As a result, we also observed an increase in the accuracy and consistency of task performance through an analytical method based on uncontrolled manifold (UCM) hypothesis (Scholz & Schoner, 1999; Scholz et al., 2000). Through this, we confirmed the effect of multi-finger interaction caused by motor redundancy (Kim et al. 2018).

These redundant motor systems exist in various hierarchies of the human motor system (Latash, Scholz, Danion & Schöner 2001), and most motor tasks

experienced in everyday life or sporting fields also require the control of redundant motor systems (synergy) through multiple hierarchies. This hierarchical control theory of the human motor system has been mentioned in several studies (Bernstein, 1967; Gorniak et al., 2007; Scholz & Latash, 1998). Previous studies have demonstrated that the output of a hierarchically higher synergy acts as the input of the hierarchically lower synergy and interacts with each other. The experimental implementation of this hierarchical system was conducted in various ways such as prehension studies (Baud-Bovy and Soechting 2001; Gao et al. 2005; Shim et al. 2005; Zatsiorsky et al. 2003) and two-hand finger pressing tasks (Kang et al., 2004; Gorniak et al., 2007).

Looking at the hierarchical control system in relation to the finger force production task using both hands, the hierarchical control level can be divided into two levels. One is the level of bimanual control of both hands and the other is the multi-finger control of each hand. Previous studies have reported a tendency to interact each other to stabilize specific task performance through these two hierarchical levels (Kang et al., 2004; Gorniak et al., 2007; Li et al., 2002). In general, multi-finger synergy appears in one-handed pressing tasks. In contrast, Gorniak et al. (2007) reported a relatively strong synergy in the upper hierarchy (bimanual level) through a two-finger pressing task, and reported a decrease or disappearance of the synergy effect at the multi-finger level. Li et al. (2002) also reported strong interference effects between hand actions when switching from one hand multi-finger action to a two-hand action. Besides Kang et al. (2004) explained that the synergy effect at the lower hierarchy which associated with a positive change in performance can be increased through appropriate practice. As such, a human movement system with motor redundancy performs a task not only by interaction

within each hierarchy but also by interaction between the hierarchies.

Archery is a sport that uses both hands and multi-finger. It controls the net force on the bow string and bow orientation by stabilizing the force distributed to both hands and each finger. Thus, archery can be a representative example of the hierarchical motor redundancy that can be experienced in sporting situations. In this study, we tried to confirm the control mechanism of the hierarchically redundant human motor system through experimental tasks similar to the arching shooting. The following four hypotheses were set to determine whether the benefits of increasing kinetic DOF observed at the multi-finger level could be extended to the hierarchical synergy levels. 1) Synergic characteristics will appear at both multi-finger level (lower hierarchy) and bimanual level (upper hierarchy). 2) Increasing the kinetic DOF of the multi-finger level will increase the synergy indices of the multi-finger and bimanual levels. 3) Increasing the kinetic DOF of the multi-finger level will increase the shooting performance of the task. 4) Both hierarchies of synergy will contribute positively to the performance of the task. To test this hypothesis, we analyzed intra-subject trial-to-trial variability of force and moments of force generated at bimanual level (upper hierarchy) and multi-finger level (lower hierarchy) through different finger DOF conditions. This approach is based on the idea that when the CNS organizes human movement, it prefers family of solutions to one unique solution for redundant motor tasks. Therefore, analyzing the family of solutions in repeated trials when performing the same motor task can identify the CNS's strategy for resolving motor redundancy. In addition, we analyzed the accuracy and precision indices to determine the successful performance at the behavior level by the addition of the kinetic DOF and the hierarchical organization of the controller. This approach may provide empirical evidence to support the theory

of motor abundance (Latash, 2000; Latash & Zatsiorsky, 2009) by identifying whether the CNS's organizational strategy for addressing motor redundancy can be used rather beneficially to successfully perform a given task.

5.2. Methods

5.2.1. Subjects

In this study, eight right-handed men (age 30.5±3.1 yrs, height 1.72±2.95 m, weight 73.1±6.6 kg) participated. All participants were selected as those who did not have a history that could functionally affect the entire upper body including the arms, hands, and fingers. This study was conducted after obtaining approval from the institutional review board (IRB No. 1703 / 002-006).

5.2.2. Equipment

5.2.2.1. Maximum voluntary contraction (MVC) task

Before performing the main experimental task of this study, maximum voluntary contraction (MVC task) was performed in advance so that each participant could perform the same level of task based on finger forces using a frame which was same as used in main task (hierarchical force production and release task)

5.2.2.2. Hierarchical force production and release task

The main task of this study was a hierarchical force production and release

task, using a frame of 820 × 150 mm (adjusted according to the participant), which was made by reproducing the physical characteristics of the archery (Figure 5-1a). Five 6-axis small force/torque transducers mounted on the frame were used. Four transducers (Nano-17, ATI Industrial Automation Garner, NC) with a diameter of 17 mm were used to measure the force of the pulling fingers, and one transducer (Nano 25, ATI Industrial Automation Garner, NC) with a diameter of 25 mm was used to measure the force of the bow hand holding the handle of the bow. Each transducer was aligned so that the direction of pressing was perpendicular to the direction of gravity, and fixed at 20 mm intervals on the vertical direction (y-axis). Finely round-shaped caps (Polylactic acid material) were inserted into the surface of the transducers so that intentional roll or slide of fingertips could be done naturally when performing the task. A magnetic sensor (Liberty Latus, Pollhemus, Colchester, VT) was attached to the front of the frame so that the angle of the frame could be measured and presented as a visual feedback to the participants in real time. The weight of the frame with all measuring devices is 1.53 kg, and the z-axis length between the force application points of both hands is about 660 mm. The center of mass of the frame is located about 220 mm (33%) from the contact surface of the bow hand to the shooting hand in the z-axis direction, and respect to the x- and y-axis directions is centered.

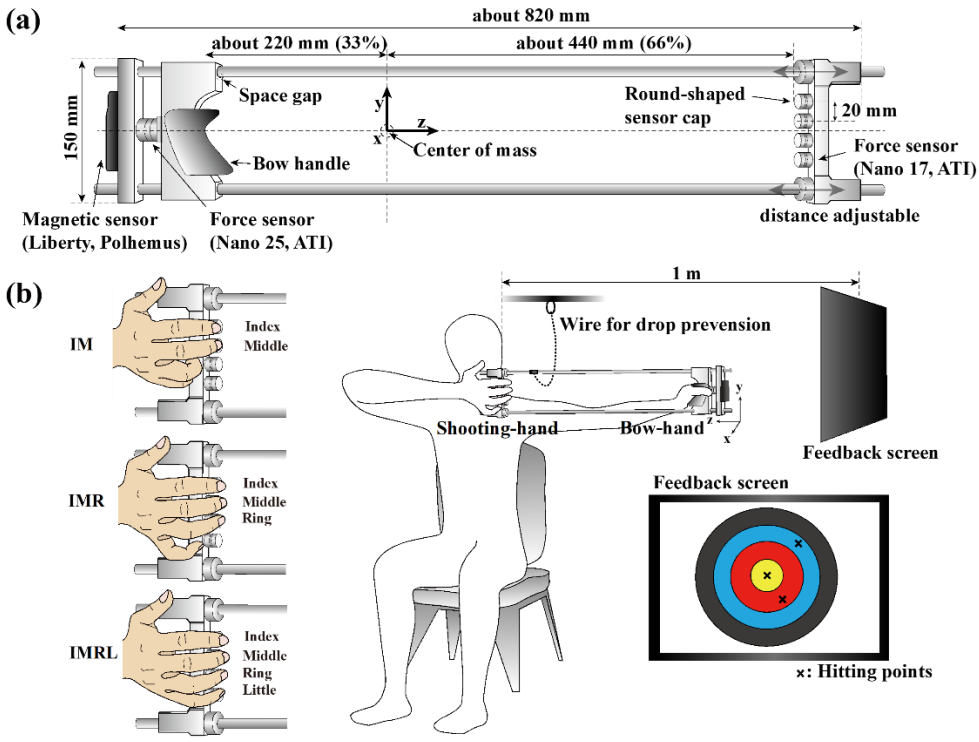

Figure 5-1. An illustration of the experimental equipment and conditions. (a) The transducers were attached to both sides of the experimental frame (size: about 820 × 150 mm). (b) Hand and finger configurations for three experimental conditions. The computer screen showed total force of involved fingers (F_{TOT}) and the frame angle controlled by the participants according to the global coordinate. After the completion of a particular trial, the feedback screen showed a hitting point of the virtual ball by assuming that the trajectory of the ball was determined by the velocity at the moment of release and gravitational force (g = 9.81 m/s^2) acting on the ball. The wire was connected to the frame to prevent the frame from dropping so that unnecessary force generation was not required on the bow hand after the release.

Analog signals from the force transducers were digitized via an analog-to-digital converter (NI USB-6225, National Instruments, Austin, TX) and sent to the computer along with the magnetic sensor signal. During the experiment, a self-configured program was used to collect data and provide visual feedback to the participants using programming software (LabVIEW 2015, National Instruments,

Austin, TX), and all data were collected at 100 Hz. The real-time visual feedback was provided to the participants in real-time via a 27-inch monitor screen (Dell, Round Rock, TX) fitted to the participant's eye level at a distance of about 1 m from the participant (Figure 5-1b). The refresh rate of the feedback screen was 60 Hz.

5.2.3. Measurement

5.2.3.1. Maximum voluntary contraction (MVC) task

Prior to the main experiment, the participants performed the maximal voluntary contraction (MVC) task. The participants were placed in a sitting position with their trunk upright on a height-adjustable chair and performed the task in the same position as the main task. The participants were generated maximum isometric contraction force for 5 seconds without rebound with four fingers on each transducer mounted on the frame. We collected force values of each finger (MVC_i, i = {index, middle, ring, little}) when the total finger force (MVC_{TOT}) was reached maximum force. After performing two trials repeatedly, the larger of the collected values was used.

5.2.3.2. Hierarchical force production and release task

The hierarchical force production and release task, which is the main task of the research, is similar to the aiming and release behavior of the archery. For the experiment, each participant carried the transducer attached frame with both hands. The experimental task was proceeded holding the handle grip on the frame, and pressing the transducers arranged in the vertical direction (*y*-axis) with each finger

of the right hand. The subjects performed a task of pressing the transducers as if pulled with the fingers (aiming) and quickly separating the fingers from the transducers (release) in three different finger degrees of freedom (IM: index-middle, IMR: index-middle-ring, IMRL: index-middle-ring-little) of the right hand (Figure 5-1b). During the task, each finger had its proximal interphalangeal joints naturally flexed to about 10 - 20°. In the IM and IMR conditions, the fingers not participating in the task were naturally flexed so that they did not touch the transducers or frame during the task. During the experiment, participants were placed in a sitting position with their trunk upright on the height-adjustable chair, and the direction in which the virtual balls were projected is set to the left of the participant so as to enable a comfortable pulling action. The elbow on the bow hand side was fully extended, and the distance between the sensors on both sides of the frame was adjusted so that the shooting hand could reach the center of the chest. In order to exclude the contribution of the lower limb, the hip and knee joints were flexed about 90° and the two feet were kept parallel to the shoulder width. The coordinates set in the transducer were defined as the direction in which the virtual ball is projected, the *x*-axis as the mediolateral direction, the *y*-axis as the vertical direction, and the *z*-axis as the anteroposterior direction (Figure 5-1b).

This task is divided into the aiming segment and the release segment, in which the first 5 seconds of the aiming segment produces a constant pulling force (*z*-axis force) and keep it constant, and by releasing the fingers as soon as possible within the remaining 5 seconds, the release segment. For the aiming segment (first 5 seconds), the force magnitude that the participants must maintain (reference force, F_{REF}) is assumed to be the amount of energy stored in the bow. And the F_{REF} was set to 50% of the MVC force of the involved fingers according to each finger

combination. The direction in which the virtual ball was projected was defined as the orientation of the frame measured by the magnetic sensor, and the angle of the frame during the aiming segment was required to be maintained at 0° (the frame is horizontally turned forward).

The release of force allowed the participant to begin self-paced. Each participant was asked to perform 20 trials for each finger combination. The rest between the conditions was set to 5 minutes, and the rest between the trials was set to 10 seconds or more. The information provided as real-time feedback through the front monitor screen included the time information indicating the time of each segment of the task, the force value to be maintained during the aiming segment, and the angle change of the frame (Figure 5-1b). During the task, there was no force affecting the frame other than the force by the bow hand (F_B of Equation 5-1) holding the frame and each finger force (F_i of Equation 5-1) of the hand pulling the sensor. In order to maintain the static equilibrium of the bow (frame assuming the bow) independent from the ground during the aiming segment, the physical constraints of all forces and moment of forces applied to the frame by these two hands must be satisfied.

First, the sum of the *x*-axis and *z*-axis components of all the forces applied to the frame must be zero, and the sum of the *y*-axis components should be the same in magnitude as the gravity applied to the frame and the opposite direction.

$$F_B^x + \sum F_i^x = 0 \qquad \text{(equation 5-1)}$$

$$F_B^y + \sum F_i^y = -mg \qquad \text{(equation 5-2)}$$

$$F_B^z + \sum F_i^z = 0 \qquad \text{(equation 5-3)}$$

, where, F_B = force of bow-hand, i = {I, M, R, L}, m = mass of frame, g = gravity.

Second, the resultant moments of the *x*-axis (M_X) and *y*-axis (M_Y) components applied to the frame should also be zero.

$$\left[\sum M_x, \sum M_y \quad \right] = [0, 0] \qquad \text{(equation 5-4)}$$

, where, Mi = moment of each axis.

5.2.4. Data analysis

MATLAB (MathWorks Inc., Natick, MA, USA) codes were used for data analysis. All measured force values were filtered using a zero-lag 4th-order low-pass Butterworth filter (cutoff at 10 Hz). The virtual ball projected through the force release assumed as the mass point has no volume, and it was assumed that the external force affected the virtual ball was only gravity. The position coordinates of the virtual balls reaching the virtual target were determined by the respective axis (*x*-, *y*-, *z*-axis) components of the ball initial velocity. It was assumed that the energy is stored in the virtual bow by the amount of force (pulling finger force) measured on the transducers through the aiming segment. When the release is made without delay, the energy stored in the virtual bow is used to move the virtual ball to the virtual target without loss. That is, if there is no error between the force value and the frame orientation in the aiming segment, and the release of the force becomes the form of the step function (the force release time is 0), the virtual ball was set to hit

the center of the virtual target. The initial velocity of the virtual ball was calculated based on the assumption of the magnitude of the force measured at the time t_0 at which the release of the force is started. We assumed that the coefficient of elasticity of the virtual bow was 0.7 N/m, and the virtual ball weight was 1 kg. The energy loss during the release of the finger force was calculated assuming that the initial velocity of the virtual ball was affected by the integral of the force (momentum) during the release. The potential energy stored in the virtual bow was assumed to be converted to the kinetic energy of the virtual ball without loss, and the initial velocity of the ball was calculated using the following equation (Equation 3-1). The velocity was calculated for the *x*-, *y*-, and *z*-axis components, respectively, and the *y*-axis component was considered to have a gravitational acceleration of -9.81 m/s^2. In this case, the force value of tangential components for calculating the velocity of the *x*- and *y*-axis components was defined as sin θ (θ = *y*-, *x*-axis angle of the frame measured by the magnetic sensor) of the *z*-axis force value. The onset at which the release of force was started was defined as the point at which 5% of the maximum rate of force change (first-derivative of the *z*-axis component of the finger force) (Olafsdottir et al., 2005). The analysis of the data was done in two analysis phases. The first phase for analysis was defined as a phase from -150 ms to -50 ms based on the t_0, the steady-state phase (SS phase). The second phase is defined as the phase from the time t_0 to the time when the finger force was 0 N, the force drop phase (FD phase). The variables calculated in this study are performance indices and synergy indices.

5.2.4.1. Task performance indices

There are task performance indices such as the coefficient of variation (CV)

and root mean square error (RMSE) of the force value observed in the steady-state (SS) phase, releasing time (RT) of the force drop (FD) phase, Accuracy index (ACI) for the center of the virtual target, and the precision index (PRI) of the point where the virtual ball reached the target during the repetitive trials.

CV was defined as the standard deviation of the force values of both hands (F_B and F_V) divided by the mean in the SS phase. And RMSE was the value obtained by quantifying the difference between the reference force (F_{REF}) and the measured force value during the SS phase, and was normalized to the magnitude of each target force value ($RMSE_{NORM}$, Equation 3-2, Chapter 3).

RT was defined as the time required for the FD phase.

Accuracy (ACI_{NORM}) and precision index (PRI_{NORM}): The accuracy index (ACI) was quantified as an average Euclidean distance between the hitting position of the virtual ball and the center of the virtual target across repetitive trials using Equation 3-3 (Chapter 3). The precision index (PRI) was quantified as an average Euclidian distance between the hitting position of the virtual ball and mean hitting position across repetitive trials using Equation 3-4 (Chapter 3). The ACI and PRI were further normalized by the reference force (F_{REF}).

5.2.4.2. synergy indices

The synergy indices were divided into the upper hierarchy synergy index (UH_ΔV), which quantifies the bimanual synergy between the two hand forces, and the lower hierarchy synergy index (LH_ΔV), which quantifies multi-finger synergy between pulling finger forces. We used analytical methods based on the uncontrolled manifold (UCM) hypothesis to quantify the synergy indices (ΔV_F, ΔV_M) for the resultant force (F_{TOT}) and resultant moment of force (M_{TOT}), where each hand or each

finger force was assumed to stabilize. For the analysis, the force data collected from each transducer through repeated trials were arranged based on t_0. We assumed each element variable to stabilize the above two performance variables (F_{TOT}, M_{TOT}) as the force value measured by each transducer and the moment of force value by it.

The element variables for calculating the synergy indices of upper hierarchy (UH_ΔV) was the force of each hand (F_B: bow-hand force, F_V: virtual finger force) or the moment of force (assume that the center of mass of the frame is the center of rotation) by each force (M_B: moment of force by bow-hand, M_V: moment of force by virtual finger). In the case of pulling hands, the effects of each finger are summed and defined as a virtual finger force (F_V). The M_{TOT}, which was one of the performance variables, was calculated by multiplying each force magnitude by the moment arm of the force application point rather than the value measured from the transducers. The moment arm of the upper hierarchy was assumed to be the distance from the center of mass of the frame to the force application point of each hand. The moment of force around the *x*-axis includes both the moment of force due to the *y*-axis force and the *z*-axis force by each of the hands, and the moment of force around the *y*-axis included both the moment of force due to the *x*-axis force and the *z*-axis force by each of the hands. For the moment of force due to the *z*-axis force, the moment arm generated by the movement of the center of pressure was multiplied by the *z*-axis force.

The factors for calculating the lower hierarchy synergy index (LH_ΔV) were the force of each finger (F_I, F_M, F_R, F_L) of the pulling hand or the moment of force of each finger (M_I, M_M, M_R, M_L). It was assumed that the virtual center of rotation for calculating the M_{TOT} by multiple fingers was the midpoint of the application points of each finger force. The force application point of each finger was assumed

to be fixed on the surface of each transducer, and each moment arm was set to the distance from the virtual center of rotation.

The synergy index of this study was an indicator for determining whether each element variable is covaried in a form stabilizing the performance variable. In order to do this, it is necessary to divide the variance of each element variable into the variance on the space that stabilizes the performance (UCM space) and the variance on the space perpendicular to the UCM space (ORT space).

The UCM space was obtained by calculating the null space of the Jacobian vector (J in Equation 4-1) as the space in which the change of the element variable (*d*EV in Equation 4-1) does not cause the change of the performance variable. In other words, the change of the element variables is a space that does not cause a change in the performance variable (*d*PV in Equation 4-1), F_{TOT} or M_{TOT}. On the other hand, the ORT space is a space in which the *d*EV causes a change in *d*PV, that is, an error (Equation 4-1).

The variance on the UCM space (V_{UCM}) and the variance on the ORT space (V_{ORT}) of the element variables were calculated for each time point, and the synergy index (ΔV) was quantified by the relative magnitude of V_{UCM} (Equation 4-7).

The variance of each space (V_{UCM}, V_{ORT}) was normalized by the DOF of the space (dimensionality) allowing comparison between each ΔVs. the ΔVs were log-transformed using the Fischer transformation applied for the computational boundaries (i.e., -2 to +2 for the UH_ΔV and IM condition of the LH_ΔV, from -3 to +1.5 for the IMR, and from -4 to +1.33 for the IMRL condition of the UH_ΔV).

5.2.5. Statistical analysis

The results are presented as mean and standard error. The repeated-measure ANOVAs were used to statistically evaluate the effects of the calculated synergy indices (LH_ΔV_F, LH_ΔV_M, UH_ΔV_F, UH_ΔV_M) and task performance indices ($RMSE_{NORM}$, RT, ACI, PRI) respectively. Factors were *Level of hierarchy* (two levels: UH, LH), *finger DOF* (three levels: IM, IMR, IMRL), and *hand* (two levels: F_B, F_V), were included in the analysis selectively according to the particular statistical tests. The intra-class correlation coefficients (ICC) as a test-retest reliability index for repetitive measurements of force values for each axis were found to be more than 0.9 (p <.001) in all conditions. Mauchly's sphericity test was used to confirm the assumptions of sphericity, and the Greenhouse-Geisser correction was applied when the sphericity assumption was rejected. For the post-hoc test, multiple pairwise comparisons with Bonferroni correction was conducted, and Linear regression analysis was used to confirm the correlation between the variables. All statistical significance levels were set at $p < 0.05$.

5.3. Results

5.3.1. Performance indices

5.3.1.1. Normalized RMS error ($RMSE_{NORM}$)

The root mean squared error of finger forces normalized by reference force ($RMSE_{NORM}$) during a steady-state force production was relatively larger in the z-axis (i.e., the axis of normal force) compared to the $RMSE_{NORM}$ of the other two axes. In addition, the $RMSE_{NORM}$ decreased with the number of fingers (DOFs) especially

in *z*-axis component. A two-way repeated measure ANOVA supported these findings with factors *Level of hierarchy* (two levels: UH, LH) and *Finger DOF* (three levels: IM, IMR, and IMRL), which showed significant main effects of *Level of hierarchy* ($F_{[1,8]} = 6.74$, $p = 0.032$, $\eta p^2 = 0.46$) and *Finger DOF* ($F_{[2,16]} = 8.06$, $p = 0.004$, $\eta p^2 = 0.50$) without significant factor interaction on *z*-axis component. Pairwise comparison confirmed that the $RMSE_{NORM}^{Z}$ of IM < IMR < IMRL for all level of hierarchy ($p < 0.05$). However, there were no significant difference within each finger DOF conditions and factor interactions on *x*- and *y*-axis component.

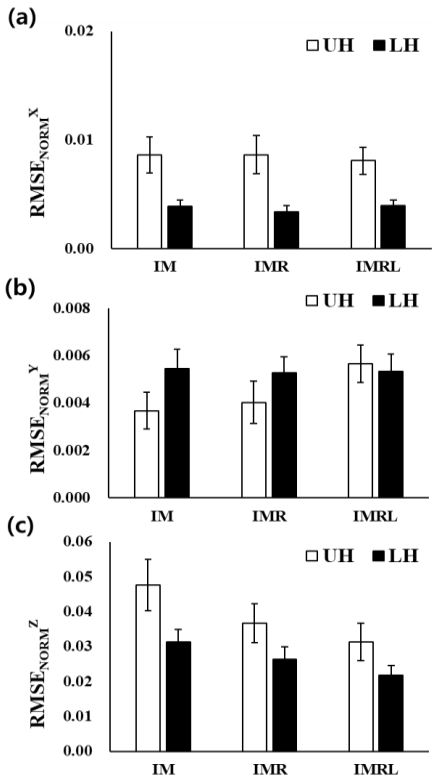

Figure 5-2. $RMSE_{NORM}$ at the steady-state force production for the *x-, y-,* and *z*-axes are presented for the upper hierarchy (white bars), and lower hierarchy (black bars) of each conditions. Values are means ± standard errors across subjects.

5.3.1.2. Coefficient of variation (CV)

Coefficient of variation (CV) of normal force for each hand during a steady-state force production was decreased with the number of finger DOFs for both hands.

A two-way repeated measure ANOVA supported these findings with factors *hand* (two levels: F_B, F_V) and *Finger DOF*, which showed significant main effects of hand ($F_{[1,8]} = 6.28$, $p = 0.037$, $\eta p^2 = 0.44$) and *Finger DOF* ($F_{[2,16]} = 5.25$, $p = 0.018$, $\eta p^2 = 0.40$) with significant *hand* × *Finger DOF* ($F_{[2,16]} = 7.35$, $p = 0.005$, $\eta p^2 = 0.48$). The significant *hand* × *Finger* reflected the fact that the effect of hand was significant only at the IM condition. Post-hoc pairwise comparison confirmed that the CV of F_B > F_V for IM condition only ($p < 0.05$).

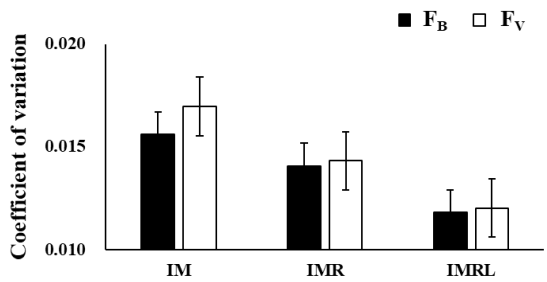

Figure 5-3. Coefficient of variation (CV) at the steady-state force production for the bow hand force (F_B), and virtual finger force (F_V) are presented for each conditions. Values are means ± standard errors across subjects.

5.3.1.3. Release time

The participants performed 20 repetitive trials for the multi-finger force production and release task for each DOF condition. Generally, there was no significant difference in the average release time across the trials between the conditions.

5.3.1.4. Performance indices (ACI_{NORM}, PRI_{NORM})

The indices of accuracy (ACI_{NORM}) and precision (PRI_{NORM}) decreased with the number of finger DOFs (i.e., the larger the number of fingers for the task, the better accuracy and precision for the performance). These findings were supported

by one-way repeated measure ANOVAs with factor *Finger DOF* (three levels: IM, IMR, and IMRL) on ACI ($F_{[2, 16]} = 52.41$, $p < 0.001$, $\eta p^2 = 0.87$) and PRI ($F_{[2, 16]} = 6.70$, $p = 0.007$, $\eta p^2 = 0.46$). Post-hoc pairwise comparisons confirmed that the ACI of IM > IMR > IMRL, and the PRI of IM > IMR, IMRL ($p < 0.05$).

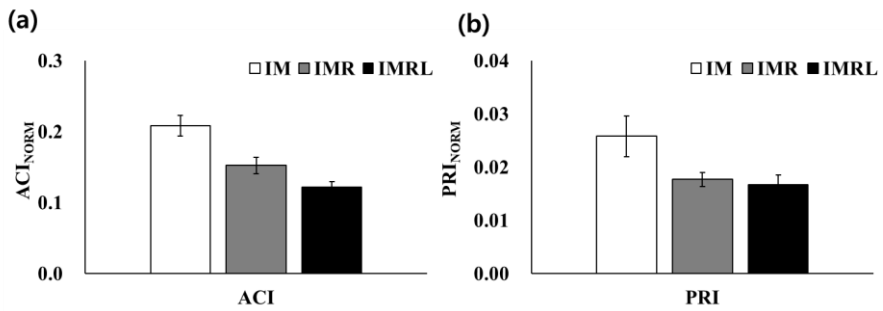

Figure 5-4. Accuracy index (ACI_{NORM}, a), the mean displacement of the location of the virtual projectile from the center of the virtual target for each finger combination (IM, IMR, and IMRL), and precision index (PRI_{NORM}, b), the mean distance of the location of the virtual projectile in a given trial from the mean location of the virtual projectile in previous trials. The data from the eight participants are presented as means and standard errors.

5.3.2. Synergy indices

5.3.2.1. Force stabilization hypothesis

First, we quantified each component of variances per DOF stabilization hypothesis (V_{UCM}^F and V_{ORT}^F) between the hierarchies and conditions for each axis. The variances were normalized by the square of the relevant reference force (F_{REF}) about the *z*-axis.

In general, The V_{UCM}^F of the lower hierarchy were larger than those of the upper hierarchy. The V_{UCM}^F decreased with the number of finger DOFs for all axes.

Two-way repeated measure ANOVAs with factors *Level of hierarchy* (two levels: UH, LH) and *Finger DOF* (three levels: IM, IMR, and IMRL) was performed separately on each axis component of variances. The results showed significant main effects of *Level of hierarchy* ($V_{UCM}^{F}\_X$: $F_{[1, 8]} = 37.28$, $p < 0.001$, $\eta p^2 = 0.82$; $V_{UCM}^{F}\_Y$: $F_{[1, 8]} = 62.66$, $p < 0.001$, $\eta p^2 = 0.89$; $V_{UCM}^{F}\_Z$: $F_{[1, 8]} = 22.35$, $p = 0.001$, $\eta p^2 = 0.74$) and *Finger DOF* ($V_{UCM}^{F}\_X$: $F_{[2,16]} = 6.82$, $p = 0.007$, $\eta p^2 = 0.46$; $V_{UCM}^{F}\_Y$: $F_{[2, 16]} = 14.01$, $p < 0.001$, $\eta p^2 = 0.64$; $V_{UCM}^{F}\_Z$: $F_{[2, 16]} = 11.61$, $p = 0.001$, $\eta p^2 = 0.59$) with significant *Level of hierarchy* ×*Finger DOF* for *x*- and *y*-axis components ($V_{UCM}^{F}\_X$: $F_{[2,16]} = 6.36$, $p = 0.008$, $\eta p^2 = 0.45$; $V_{UCM}^{F}\_Y$: $F_{[2, 16]} = 16.42$, $p < 0.001$, $\eta p^2 = 0.67$). The significant *Level of hierarchy* ×*Finger DOFs* reflected the fact that the tendency according to the factor *Finger DOF* is stronger for the lower hierarchy. Post-hoc pairwise comparison confirmed $V_{UCM}^{F}\_X$ of IM > IMRL for the upper hierarchy, and $V_{UCM}^{F}\_X$ of IM > IMR, IMRL and $V_{UCM}^{F}\_Y$ of IM > IMR, IMRL for the lower hierarchy ($p < 0.05$). Generally, The V_{ORT}^{F} was decreased with the number of finger DOFs and the tendency of decreasing V_{ORT}^{F} appears to be stronger in the lower hierarchy. Two-way repeated measure ANOVAs with factors *Level of hierarchy* and *Finger DOF* was performed separately on each axis component of variances. The results showed significant main effects of *Level of hierarchy* on V_{ORT}^{F} of *y*-axis ($F_{[1, 8]} = 14.79$, $p = 0.005$, $\eta p^2 = 0.65$) and *Finger DOF* on V_{ORT}^{F} of *x-, and z*-axis ($V_{ORT}^{F}\_X$: $F_{[2,16]} = 7.85$, $p = 0.004$, $\eta p^2 = 0.50$; $V_{ORT}^{F}\_Z$: $F_{[2, 16]} = 9.73$, $p = 0.002$, $\eta p^2 = 0.55$) with significant *Level of hierarchy* ×*Finger DOF* for *x*- and *z*-axis components ($V_{ORT}^{F}\_X$: $F_{[2,16]} = 17.57$, $p < 0.001$, $\eta p^2 = 0.69$; $V_{ORT}^{F}\_Z$: $F_{[2, 16]} = 4.95$, $p = 0.021$, $\eta p^2 = 0.38$). The significant *Level of hierarchy* ×*Finger DOFs* reflected the fact that the tendency according to the factor *Finger DOF* is appears to be in the lower hierarchy only. Post-hoc pairwise comparison confirmed $V_{UCM}^{F}\_X$ of IM

>IMR, IMRL and $V_{UCM}{}^{F}\_{Z}$ of IM > IMR > IMRL for the lower hierarchy only, and UH_$V_{UCM}{}^{F}_{X}$ < LH_$V_{UCM}{}^{F}_{X}$ for the IM condition only ($p < 0.05$).

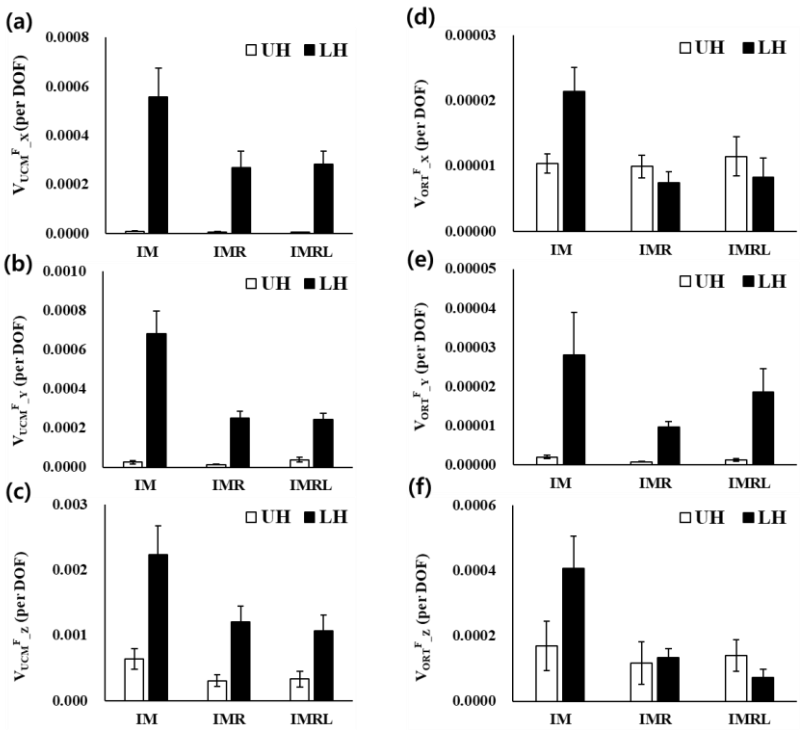

Figure 5-5. Two component of variances related to F_{TOT} stabilization, V_{UCM} and V_{ORT} per degree-of-freedom, in the finger force space are presented for *x*-axis, *y*-axis, and *z*-axis for each hierarchy (UH, LH). Values are means ± standard errors across subjects.

We quantified the indices of force stabilization synergies for the upper and lower hierarchies (UH_ΔV_F, LH_ΔV_F) during the steady-state force production. In general, the ΔV_F of the lower hierarchy were larger than those of the upper hierarchy. In the case of $\Delta V_F{}^{X}$ and $\Delta V_F{}^{Z}$, the trends of the upper and lower hierarchies were the opposite.

These findings were supported by a two-way repeated measure ANOVA on ΔV_F setting factors as *Level of hierarchy* and *Finger DOF*. The results showed

significant main effects of *Level of hierarchy* (ΔV_F^X: $F_{[1, 8]} = 282.02$, $p < 0.001$, $\eta p^2 = 0.97$; ΔV_F^Y: $F_{[1, 8]} = 9.95$, $p < 0.001$, $\eta p^2 = 0.55$; ΔV_F^Z: $F_{[1, 8]} = 20.41$, $p = 0.002$, $\eta p^2 = 0.72$), *Finger DOF* on ΔV_F^Y ($F_{[2,16]} = 8.95$, $p = 0.002$, $\eta p^2 = 0.53$), and *Finger DOF* on ΔV_F^Z ($F_{[2,16]} = 5.17$, $p = 0.019$, $\eta p^2 = 0.39$). There were significant *Level of hierarchy* ×*Finger DOF* for ΔV_F^X ($F_{[2,16]} = 21.82$, $p < 0.001$, $\eta p^2 = 0.73$) and ΔV_F^Z ($F_{[2,16]} = 28.47$, $p < 0.001$, $\eta p^2 = 0.78$). The significant *Level of hierarchy* ×*Finger DOFs* reflected the fact that the tendency according to the factor *Finger DOFs* is appears to be opposite between the upper and lower hierarchies. Post-hoc pairwise comparison confirmed the UH_ΔV_F of IM >IMRL and the LH_ΔV_F of IM <IMR, IMRL for the *x*-axis, and the UH_ΔV_F of IM >IMR and the LH_ΔV_F of IM <IMR<IMRL for the *z*-axis ($p < 0.05$).

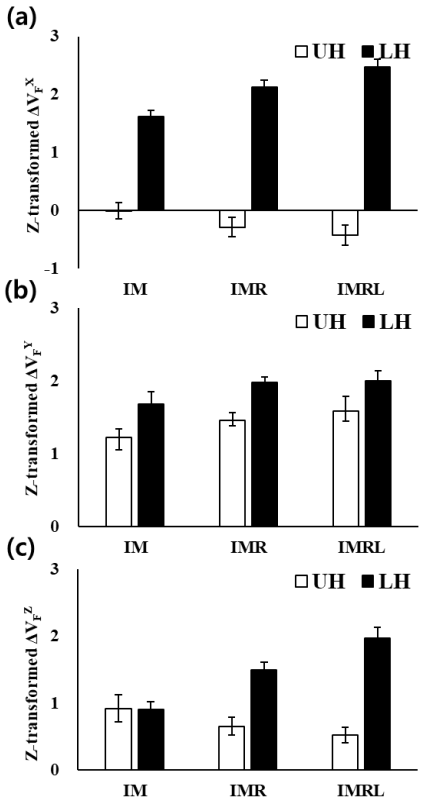

Figure 5-6. Z-transformed synergy indices with respect to F_{TOT} stabilization, ΔV_F, for the UH (white bars), and LH (black bars) at the *x-, y-,* and *z*-axes for each condition. Values are means ± standard errors across the subjects.

5.3.2.2. Moment stabilization hypothesis

We computed the moment stabilization synergies for the upper and lower hierarchies (UH_ΔV_M, LH_ΔV_M) during the steady-state force production. Note that the element variables for calculating the UH_ΔV_M are the moments of forces for both hands, and these values include the effects of changes in the center of pressure (COP) of bow hand force (F_B) and virtual finger force (F_V), and there was no statistical correlation between each force magnitude and COP measured in this study. The UH_ΔV_M^Z and the LH_ΔV_M^Y are assumed to be zero. In general, the ΔV_M increased with the number of fingers for all axis components. Two-way repeated measure ANOVA with factors *Level of hierarchy* and *Finger DOF* on ΔV_M^X showed significant main effects of *Level of hierarchy* ($F_{[1, 8]} = 24.35$, $p = 0.001$, $\eta p^2 = 0.75$) and *Finger DOF* ($F_{[2, 16]} = 38.27$, $p < 0.001$, $\eta p^2 = 0.83$) on ΔV_M^X with significant *Level of hierarchy* ×*Finger DOFs* ($F_{[2,16]} = 20.40$, $p < 0.001$, $\eta p^2 = 0.72$). The significant *Level of hierarchy* ×*Finger DOFs* reflected the fact that the tendency according to the factor *Finger DOF* is appeared to be in the lower hierarchy only. Post-hoc pairwise comparison confirmed LH_ΔV_M^X of IM < IMR, IMRL ($p < 0.05$). And one-way repeated measure ANOVAs with factor *Finger DOF* on UH_ΔV_M^Y and LH_ ΔV_M^Z showed significant main effects of *Finger DOFs* (UH_ΔV_M^Y: $F_{[2,16]} = 5.24$, $p = 0.018$, $\eta p^2 = 0.40$; LH_ΔV_M^Z: $F_{[2,16]} = 142.20$, $p < 0.001$, $\eta p^2 = 0.95$). Post-hoc pairwise comparison confirmed UH_ΔV_M^Y of IM < IMRL, and LH_ΔV_M^Z of IM < IMR < IMRL ($p < 0.05$).

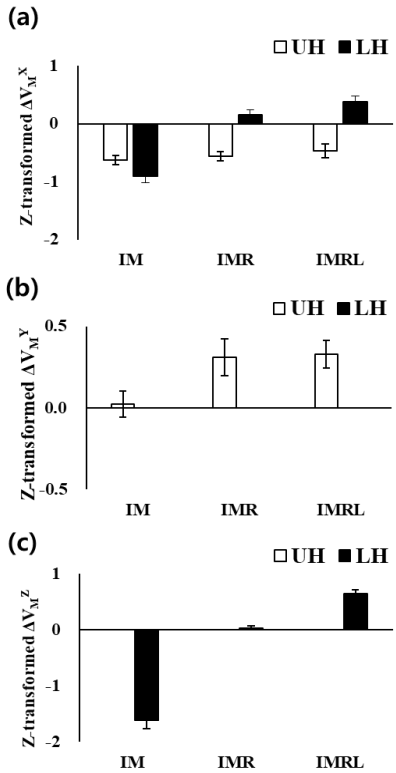

Figure 5-7. Z-transformed synergy indices with respect to M_{TOT} stabilization, ΔV_M, for the UH (white bars), and LH (black bars) at the *x*-, *y*-, and *z*-axes for each condition. Values are means ± standard errors across the subjects.

5.3.3. The comparison between synergy indices and performances indices

Figure 5-8 illustrates the findings for the sets of force stabilizing synergy indices (e.g., UH_ΔV_F and LH_ΔV_F) and the variables associated with the accuracy index (ACI) as a performance index across all individual participants and conditions. In most of the cases in LH_ΔV vs. ACI, there were negative correlations between the synergy indices and ACI across participants and conditions (i.e., the larger synergy indices, the better accuracy). The coefficient of correlation (*r*) was significant in LH_ΔV_F^X vs. ACI and LH_ΔV_F^Z vs. ACI (r = -0.62 for LH_ΔV_F^X, r = -0.69 for LH_ΔV_F^Z). However, in the cases of UH_ΔV vs. ACI, there were positive correlations between the synergy indices and ACI across participants and conditions

except for UH_ΔV_F^Y vs. ACI which showed a negative correlation. The coefficient of correlation (*r*) was significant in UH_ΔV_F^X vs. ACI and UH_ΔV_F^Y vs. ACI than the UH_ΔV_F^Y vs. ACI (*r* = 0.63 for UH_ΔV_F^X, *r* = -0.46 for UH_ΔV_F^Y).

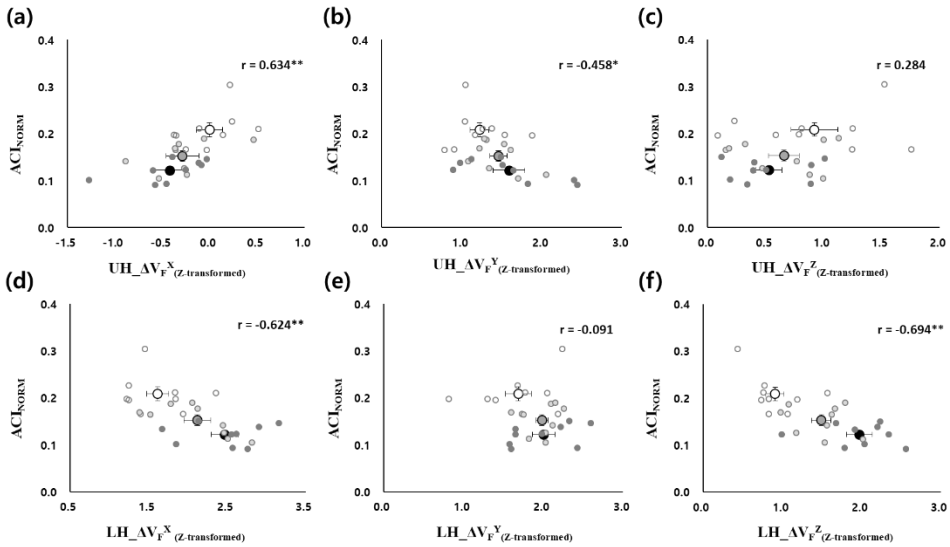

Figure 5-8. Correlation between the synergy indices of F_{TOT} stabilization for three axes (i.e., ΔV_F^X, ΔV_F^Y, and ΔV_F^Z) and (a~c) accuracy index (ACI) and (d~f) precision index (PRI). Small dots represent individual subject data for the IM (white), IMR (gray), and IMRL (black) conditions. The coefficient of determination (r-value) are shown. The average values across subjects for the IM (white), IMR (gray), and IMRL (black) condition are presented with standard error bars in large circles.

5.4. Discussion

In our previous study, we confirmed that the increase in kinetic DOF causes positive changes in task performance, through multi-finger force production and release tasks. These results showed a significant correlation with the strength of stability properties (i.e., synergy indices) (Kim et al., 2018). This study attempts to verify whether these features can be extended to additional mechanical constraints

(free objects control) and hierarchical levels (bimanual and multi-finger level) through four hypotheses mentioned in the introduction. As a result, an increase in kinetic DOF of the multi-finger level was accompanied by the improvement of hierarchical synergy indices and shooting performances. In addition, the force and moment stabilizing synergy indices at both hierarchical levels differed in part from previous studies. These results can be attributed to the mechanical constraints and hierarchical level characteristics of the task. Therefore, we tried to understand the results based on these two factors.

5.4.1. Hierarchical control

The synergy was introduced by Gelfand and Tsetlin (1966) as the concept of 'structural unit' and developed by Latash (2000) to the concept of “the principle of motor abundance”. Synergy is understood as a neural organization of multiple elements that stabilize a major output variable. In this study, we tried to understand the hierarchical organization of synergy. Several previous studies have been published by Pressing (Kang et al., 2004; Gorniak et al., 2007), Prehension (Baud-Bovy and Soechting 2001; Gao et al. 2005; Shim et al. 2005; Zatsiorsky et al. 2003), pointing (Domkin et al. 2002), etc., studied hierarchical synergy under various conditions, and presented inconsistent results according to the characteristics of the task. For example, Shim et al. (2003) reported that synergic characteristics were observed in both the individual finger level and the virtual finger level through the prehension task, some previous studies, studied through the bimanual finger pressing force production task, have reported synergic properties only at the upper hierarchy (bimanual level) or relatively weak synergy effects at the lower hierarchy (multi-

finger level) (Gorniak et al., 2007; Kang et al., 2004).

Gorniak et al. (2007) explained that the central nervous system (CNS) has difficulty in organizing two levels of synergy at the same time, and tried to interpret the cause of this difference as familiarity with the task. In other words, it is difficult to create a new synergy when encountering a new task rather than a familiar behavior like prehension, and Kang et al. (2004) also suggests that a lot of practice may be required for synergy to appear simultaneously at two hierarchical levels. However, the experimental results of this study showed that the subjects who participated in the experiment showed synergic characteristics in some upper hierarchy (bimanual level) and lower hierarchy (multi-finger level), even though they were people who were not familiar with archery or any task-related movements. The fact that the participants are not familiar with the task is the same as in the previous studies, and it is difficult to explain the cause of the difference in the results by being familiar with the task.

Gorniak et al. (2007) suggested only the total force of both hands as feedback in their task, without information on each hand's force, and this feedback information could also have affected the result of reduced multi-finger level synergy. The task of this study, which is a hierarchical control task, was to provide participants with the total force of the pulling hand as feedback, resulting in a stronger synergy pattern at the multi-finger level of the pulling hand. In other words, there is a possibility that the influence of the feedback given to the primary task, there is some connection with the results of the previous study. However, some previous studies have reported that visual feedback has no effect on multi-finger pressing synergies (Latash et al. 2002), and our results also show a synergic pattern at the bimanual level as well as the multi-finger level.

The task of this research is similar to that of Gorniak et al. (2007) in that both bimanual and multi-finger levels are included, However, to satisfy the task constraint, both hands have the same physical characteristics as the Prehension task (Shim et al., 2003, Zatsiorsky et al., 2003) in that the forces must be equal and opposite. This feature is a physical constraint caused by experimental conditions that control free objects rather than fixed objects. Park, Baum, Kim, Kim, and Shim (2012) confirmed that the CNS's control strategies were altered by internal and external constraints under different conditions through a multi-digit prehension task using fixed and free objects. The physical properties of free objects, which will be explained next, may help explain the results of this study.

5.4.2. Free object control

The experimental conditions of this study have the physical property that the object controlled by the finger is not a fixed frame but a free object with independent degrees of freedom. Therefore, the resultant characteristics are also partly linked to the results of the prehension study, which reported that synergic characteristics appeared simultaneously in multiple hierarchies even in the absence of visual feedback (Shim et al., 2003; Park et al. 2015). The prehension task studied in previous studies and our research task (archery like action) have a common point in that all the forces acting on the object must be compensated to satisfy the task, and This results in a positive synergy pattern between the forces of the upper hierarchy (Both hands in our study/thumb and virtual finger in prehension task). Contrary to the results of the pressing task study (Kang et al., 2004; Gorniak et al., 2007), on the other hand, the synergy index was rather large at the lower hierarchy (multi-finger

level) as well as at the upper hierarchy (bimanual level). These results can be interpreted as being due to the physical conditions of the free object control task. In this study using the free object, there are additional resultant moment constraints as well as resultant force constraints applied to the object to satisfy the static constraints of the object (Park, Baum, Kim, Kim, and Shim, 2012). An increase in task constraints means a reduction in the level of redundancy at the elemental level to satisfy the task. Kim et al. (2018) reported that, in a redundant system of multi-finger force production tasks, an increase in kinetic degrees of freedom can positively affect task performance. On the contrary, the prehension task, which is the free object control situation, and the static constraint in the present task mean that the extra degree of freedom is relatively small compared to the fixed object control situation. This may mean that additional effort is required to perform the task and may cause multi-finger level force stabilization synergy. Singh et al. (2010) reported an increase in the synergy index when one finger fatigued in a finger pressing task. That is, when some of the available degrees of freedom are damaged, the elements of the remaining degrees of freedom interact more actively. As a result of showing a positive synergy index of multi-finger level in this study or preliminary study of prehension, the increased task constraints of free object controls relative to fixed object controls may have provoked active interactions on multi-finger-level. On the other hand, the task of this study is different from the prehension task in that the magnitude of the normal force is limited by the task constraint (F_{REF}). As a result, it showed a strong negative covariation pattern between each finger force at the multi-finger level and tended to stabilize force. In addition, the results of this study show very high force stabilization synergy indices for the tangential direction (*y*-axis on UH, *x*-, *y*-axis on LH), which is similar to previous studies on prehension using free objects (Jo et al. 2015). In free

object control situations, the force components in the tangential direction influence the orientation of the object (frame), And it seems to influence participants with intuitive feedback to the participants. Therefore, the results of this study show positive force stabilization synergy indices in most directions. This result is different from the results of previous experiments (Kim et al. 2018), which were conducted in the same environment except that the frame was fixed.

5.4.3. Effect of additional DOF

Motor abundance means that the CNS positively utilizes the redundant degrees of freedom of the human body in the control process for generating motions to achieve specific task goals. This feature can be identified by checking whether redundant elements participating in particular motor tasks perform purposeful covariations. In our previous study, which simulated the archery-like shooting task, increasing the DOF of the finger has been shown to increase the synergy index which stabilizes the total force. Moreover, the increase of the synergy index with increasing DOF showed an increase with accuracy and precision of performance, and this shows that actively utilizing the extra DOF can improve stability of performance at the actual behavioral level. However, the mechanical constraints of the motor task performed in our previous study have the limitation that they are different from the actual archery task, and the independence of the finger action and sharing pattern is reported to depend on the mechanical constraints in the task (Park, Baum et al., 2012). Because this study was performed with different mechanical constraints (i.e., free object) and other demand for control (bimanual manipulation), the results can be expected to be also different. However, despite this difference in physical and control

requirements, this study showed an increase in the synergy index similar to the previous study with the increasing number of fingers at the hierarchically lower level (i.e., multi-finger level). In particular, the index of shooting performance (accuracy and precision) increased with synergy indices that stabilized finger total force. These results provide convincing evidence that, despite the differences in task characteristics associated with mechanical constraints, the controller can successfully perform the required task using abundant human DOF.

Another feature, similar to the previous study, despite the changed mechanical necessities of the task, is that the organization of variability of each finger decreases the performance error (i.e., orthogonal variance) with increasing DOF. Our previous studies have shown that the overall across-trial variance of the finger force production task in fixed object situations is reduced, but the relative magnitude of the variance in the subspace where equal performance (i.e., uncontrolled manifold) is controlled in increasing fashion, and this confirms that there is a shared part with the stochastic optimal control model (Todorov and Jordan, 2002). In our study, we found a tendency for the controller to control the human body in the direction of reducing variance by including inherent constraints on moments not given as tasks (Kim et al., 2018). This pattern also appeared in this study. In this study, the strategy to actively stabilize not only the finger force, which is the salient performance variable but also the moment by the finger force, was shown especially in IMRL condition. Because the task of this study is to free object control, multi-finger level moment control may have some effect on task performance. However, since the *z*-axis moment (Figure 5-7) does not affect performance, it tends to increase with positive synergy as the number of fingers increases, although it is not included in the task constraint, and this is evidence for supporting the above discussion.

5.5. Conclusion

This study attempts to verify that the positive contribution to task performance due to the increased degree of freedom to participate in the task can be extended to additional mechanical constraints (free object control) and hierarchical levels (bi-mechanical and multi-finger levels). The result of this study suggests that the human control system actively uses the extra degrees of freedom to stabilize the performance variables of the task, and it is confirmed that this phenomenon occurs simultaneously at the bimanual level and multi-finger level. In other words, increasing the degree of freedom at one level of hierarchy induces positive interactions across hierarchical control levels, which in turn positively affects the performance of the task.

Chapter 6. Relationship between multi-finger synergy and anticipatory postural adjustment during force production and release task

6.1. Introduction

Synergy exists across various hierarchies, and the hierarchical control theory in the human movement system has been mentioned by several researchers (Bernstein, 1967; Gorniak et al., 2007; Scholz & Latash, 1998). In the case of two-handed tasks, the hierarchical control level can be divided into two levels. One is the bimanual control of both hands and the other is the multi-finger control of each hand. We can expect that the element variables of each hierarchy (each hand or each finger) will interact to stabilize a common task performance. Several previous studies have described that when fingers of both hands cooperate with each other with a common purpose, they have a synergy effect that stabilizes task performance in bimanual level also (Kang et al., 2004; Paulignan, Dufosse, Hugon, & Massion, 1989; Scholz & Latash, 1998), and sets of muscles in two limbs can be totally controlled as a single structural unit (Castiello, Bennett, & Paulignan, 1992; Flanagan & Wing, 1993; Scholz & Latash, 1998; Werremeyer & Cole, 1997). On the other hand, the activation of the proximal and focal muscles, which occur in feedforward fashion, maybe time-varying, and synergy to stabilize performance variables may also be independent for each hierarchical level (Gorniak et al., 2007; Scholz & Latash, 1998). Therefore, it is difficult to interpret the effect of anticipation related to the performance of a task

only at a specific hierarchical level.

In general, anticipatory control mechanisms can be explained by anticipatory postural adjustment (APA) and anticipatory synergy adjustment (ASA). The traditional view of APA can be understood as generating a force or torque corresponding to the perturbation of the expected motion or posture (Massion, 1992), and ASA refers to a phenomenon in which the synergy index is reduced 200 to 250 ms before the intended action or predictable perturbation (Klous et al., 2011; H. Olafsdottir et al., 2005; Shim, Latash, et al., 2005).

According to the central back-coupling hypothesis, the CNS controls two control variables (CV1, CV2). One of them (CV1) controls the magnitude of the main performance variable associated with the nature of the task, and a predictive change in the behavior or perturbation of CV1 leads to APA. The other one (CV2) is related to the stability property of the main performance variable mentioned above, and the predictive change of CV2 leads to ASA (Latash, 2008; Latash et al., 2005). It is suggested that ASA and APA may have originated from the same neuronal mechanism in terms of delayed by simple reaction time conditions (De Wolf et al., 1998; Lee, Buchanan, & Rogers, 1987; Olafsdottir et al., 2005), or by aging and brain disorders (Olafsdottir et al., 2008; Park, Wu, et al., 2012). However, ASA differs from APA in that it is not counterproductive in predicted behavior, and CV2 (synergy) can be changed without changing CV1 (performance) (Latash, 2008; Latash et al., 2005; Scholz et al., 2000). In these two respects, APA and ASA can be understood as typical anticipatory strategies of human motion that can be controlled independently.

This study was conducted to investigate, which level of anticipatory control was affected by the anticipatory condition, and how does such a change of

anticipatory control affects the accuracy and precision of the task. Archery shooting is a hierarchical control task requiring bimanual control of bow hand and shooting hand, and multi-finger control of shooting hand. And archery shooting operations also determine performance through the creation and maintenance of accurate and stable forces and consistent release (Leroyer et al., 1993; Martin et al., 1990; Nishizono et al., 1987). Therefore, we tried to verify the following hypothesis by reproducing the shooting operation of archery as an experimental situation. First, there will be synergies of each hierarchy during aiming (bimanual synergy of both hands, the multi-finger synergy of shooting hands, and muscle synergy of each involved muscle). Second, the anticipatory control mechanism (APA and ASA) will be different depending on the release type. Third, the performance indices will be different depending on the anticipatory condition. Experimental verification of these hypotheses will help to understand the role of human anticipatory mechanisms in task performance.

6.2. Methods

6.2.1. Subjects

Eight Young adult males without any neurological pathology participated in this study (age 30.5±3.4 yrs, height 1.71±2.08 m, weight 72.1±6.3 kg). All participants were identified through the Edinburgh inventory (Oldfield, 1971) as right-handed. This study was conducted after approval of the Institutional Review Board (IRB) at Seoul National University (IRB No. 1703 / 002-006).

6.2.2. Equipment

The main task of this study was a hierarchical force production and release task, using a frame which was made by reproducing the physical characteristics of the bow (same with the chapter 5, Figure 6-1). In the body of the frame, an electromagnetic sensor (Liberty, Polhemus, LA, CA) was attached to measure the angle of the bow when aiming. The force plate (AMTI, OR-6, Watertown, MA, USA) was also used to record the moment and the vertical component of the reaction force to calculate the center of pressure (COP). The sampling rate of the force, moment and electromagnetic sensor signals was set at 100 Hz. In order to record the muscle activation level change before force release, EMG (Trigno, Delsys, Natick, MA) electrodes were attached to the 16 muscles of the participants (pectoralis major, middle trapezius, erector spinae, external oblique abdominis, gluteus medius, tibialis anterior, peroneus longus, soleus of right and left sides). The sampling rate of the EMG signals was set at 2000 Hz. A 75-inch computer screen was positioned in front of the subject, which provided real-time force feedback.

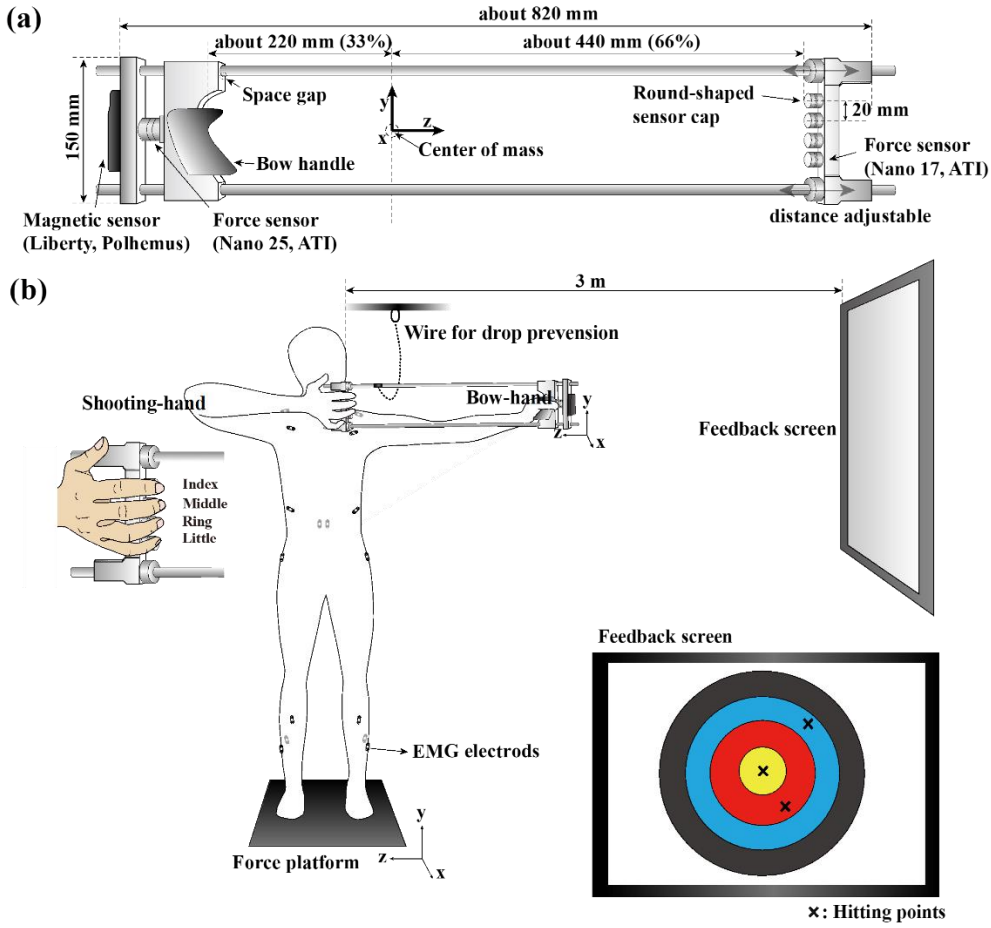

Figure 6-1. An illustration of the experimental equipment and conditions. (a) The transducers were attached to both sides of the experimental frame (details in Chapter 5). (b) Participants stood on a force platform with their feet parallel in shoulder width. The wire was connected to the frame to prevent the frame from dropping so that unnecessary force generation was not required on the bow hand after the release.

6.2.3. Experimental Procedure

6.2.3.1. Maximal voluntary contraction (MVC) task

The participants were instructed to pull the transducers mounted on the frame with all four fingers simultaneously as hard as possible until the maximum total finger force (MVC_{TOT} about the *z*-axis) was achieved. Each trial was performed for

5 s, and the real-time visual feedback of total finger force (F_{TOT}) was provided on the screen. The maximal individual finger forces (MVC_i; i = {index, middle, ring, little}) were captured at the time of MVC_{TOT}. The participants performed two consecutive trials, and the average MVC_{TOT} and MVC_i values across the two trials were used to set reference force levels for the next task.

6.2.3.2. Hierarchical force production and release task

The hierarchical force production and release task, which is the main task of the research, is similar to the aiming and release behavior of the archery. For the experiment, each participant carried the transducer attached frame with both hands. The experimental task was proceeded holding the handle grip on the frame, and pressing the transducers arranged in the vertical direction (*y*-axis) with each finger of the right hand. The subjects performed a task of pressing the transducers as if pulled with the fingers (aiming) and quickly separating the fingers from the transducers (release) with four fingers (IMRL: index-middle-ring-little) of the right hand (Figure 6-1). During the task, each finger has its proximal interphalangeal joints naturally flexed to about 10 - 20°. During the experiment, participants stood on a force plate with their feet parallel to each other at shoulder width, and the direction in which the virtual balls are projected was set to the left of the participant so as to enable a comfortable pulling action. The elbow on the bow hand side was fully extended, and the distance between the sensors on both sides of the frame was adjusted so that the shooting hand could reach the center of the chest. The coordinates set in all transducers are defined as the direction in which the virtual ball is projected, the *x*-axis as the mediolateral direction, the *y*-axis as the vertical direction, and the *z*-axis as the anteroposterior direction (Figure 6-1).

This task is divided into the aiming segment and the release segment, in which the first 5 seconds of the aiming segment produces a constant pulling force (*z*-axis force) and keep it constant, and by releasing the fingers as soon as possible within the release segment. For the aiming segment (first 5 seconds), the force magnitude that the participants must maintain (reference force, F_{REF}) is assumed to be the amount of energy stored in the bow. And the F_{REF} was set to 40% of the MVC force of the involved fingers according to each finger combination. The direction in which the virtual ball is projected is defined as the orientation of the frame measured by the magnetic sensor, and the angle of the frame during the aiming segment is required to be maintained at 0° (the frame is horizontally turned forward). The experimental conditions included three types of releasing manner 1) self-triggered manner (ST), and 2) reaction time manner (RT). RT is a way of releasing as soon as possible in response to a random signal displayed on the monitor, and ST has allowed the participant to release the force at their own pace. Each participant was asked to perform 20 trials for each finger combination. The rest between the conditions was set to 5 minutes, and the rest between the trials was set to 10 seconds or more. The information provided as real-time feedback through the front monitor screen includes the time information indicating the time of each segment of the task, the force value to be maintained during the aiming segment, and the angle change of the frame (Figure 6-1b). During the task, there is no force affecting the frame other than the force by the bow hand holding the frame and each finger force of the hand pulling the sensor. In order to maintain the static equilibrium of the bow (frame assuming the bow) independent from the ground during the aiming segment, the physical constraints of all forces and moment of forces applied to the frame by these two hands must be satisfied (F_i of Equation 5-1, 2, 3, Chapter 5). Before performing the

task, the baseline EMG value was measured in the same posture as the task posture. The EMG value measured during task execution was normalized to the baseline EMG value.

6.2.4. Data analysis

Customized codes were written to analyze the finger force and EMG data. Before variable computation, a digital zero-lag 4th-order low-pass Butterworth filter with a cutoff frequency of 10 Hz was applied to the raw force, and all EMG signals were rectified and filtered with a 20 to 450 Hz band-pass, 4th-order, zero-lag Butterworth filter. Rectified EMG signals were integrated over 1% time interval during the analysis phase. In addition, following indices of timing variable were detected within a single trial. t_0 was defined as the time moment when the first derivative of F_{TOT} (dF/dt) reached 5% of the first negative peak of dF/dt. The duration of the steady-state phase was defined as between -1500ms and -500ms prior to t_0. Changes in coordinates of the center of pressure (ΔCOP) in the anteroposterior direction (*y*-axis) were computed using the following Equation 6-1.

$$\Delta \mathrm{COP}_Y = \frac{-\Delta \mathrm{M}_Y}{F_Z} \qquad \text{(Equation 6-1)}$$

, where, ΔCOP_Y = COP shifts on *y*-axis, ΔM_Y = moment changes on *y*-axis, F_Z = vertical ground reaction force

6.2.4.1. Performance indices

Angle error at t_0: The angle error of the bow (experimental frame) according to 0° (The frame points to the center of the target and is horizontal to the ground) at t_0 was calculated.

Mean and standard deviation(SD) of FE_{t0}: Mean and standard deviation(SD) of force error et t_0 according to the F_{REF} (mean FE_{t0} and SD of FE_{t0}) were calculated.

Accuracy (ACI_{NORM}) and precision index (PRI_{NORM}): The accuracy index (ACI) was quantified as an average Euclidean distance between the hitting position of the virtual ball and the center of the virtual target across repetitive trials using Equation 3-3 (Chapter 3). The precision index (PRI) was quantified as an average Euclidian distance between the hitting position of the virtual ball and mean hitting position across repetitive trials using Equation 3-4 (Chapter 3). The ACI and PRI were further normalized by the reference force (F_{REF}).

6.2.4.2. Muscle mode (using principal component analysis)

IEMG data matrices combined over each trial for each condition separately. The correlation matrix among the IEMG was subjected to varimax rotated principal component analysis (PCA) (Krishnamoorthy, Scholz, & Latash, 2007) for each participant. The first five PCs were selected for further analysis based on that the explanatory power of the PCs is more than 80%. This means that the 12-dimensional muscle activity signal is reduced to 5 dimensions, and the muscle groups composed of the reduced dimension is defined as the muscle mode (M-mode). The magnitude (coefficient) of the M-mode is assumed to be manipulated by the controller (CNS) to produce a COP shift.

6.2.4.3. Uncontrolled manifold (UCM) analysis

The framework of uncontrolled manifold (UCM) approach was employed to quantify the bimanual (upper hierarchy) and multi-finger (lower hierarchy) synergy indices for stabilizing resultant force, and muscle mode synergy index for stabilizing COP of each involved elements. Linear relations between changes in the magnitudes of M-modes (ΔMode) and the COP shifts (ΔCOP) were assumed and the corresponding multiple regression equations. The coefficients of the regression equations were arranged in Jacobian matrix to calculate the synergy index where the M-modes stabilize the COP shift ($\Delta V_{M\text{-}mode}$).

$$\Delta COP = k_1 \Delta Mode_1 + k_2 \Delta Mode_2 + k_3 \Delta Mode_3 + k_4 \Delta Mode_4 + k_5 \Delta Mode_5;$$

$$J = [k_1 \;\; k_2 \;\; k_3 \;\; k_4 \;\; k_5] \qquad \text{(Equation 6-2)}$$

, where, ΔCOP = COP shifts, ΔMode = change of M-mode magnitude, k_i = regression coefficients

Each participant performed multiple trials for each condition, and the repetitive trial data were aligned with respect to t_0, the time initiation of F_{TOT} release. The manifold was found by computing the null space of the Jacobian of the transformation (i.e., linearly approximated null space spanned by the basis vector).

The time series of variances within two subspaces, V_{UCM} and V_{ORT} (Equation 4-7) across repetitive trials were computed for each performance variables and each condition. The UCM was defined as an orthogonal set of the unit vectors in the space of finger forces that did not change the given performance variables. The other subspace (ORT) was the orthogonal vector to the UCM. The normalized difference

between these variances is quantified by a variable ΔV by the Equation 4-7 (Chapter 4). Further, the ΔVs were log-transformed using the Fischer transformation applied for the computational boundaries (i.e., -2 to +2 for the UH_ΔVs, from -4 to +1.33 for the LH_ΔVs, from -5 to 1.25 for the $\Delta V_{M\text{-}mode}$).

ASA and APA: The time of ASA (t_{ASA}) is defined as the moment when the standard deviation value of ΔV_F for each hierarchy (UH, LH), and $\Delta V_{M\text{-}mode}$ is more than twice the steady-state force production phase. Similarly, the time of APA (tAPA) is defined as the moment when the standard deviation of the EMG value of each measured muscle or the ground reaction force (GRF) is more than twice the steady-state force production phase. And magnitude of ASA (ΔΔV) was defined as the change in ΔV from t_{ASA} to t0.

6.2.5. Statistical analysis

The data are presented as means and standard error (SE). Repeated measured ANOVAs with factors *Type of release* (two levels: ST, RT), *Axis* (three levels: x-, y-, and *z*-axis were used. Notably, we explored how the main outcome variables ($RMSE_{NORM}$, FE_{t0}, ACI, PRI, ΔVs, t_{ASA}s, t_{APA}s, magnitude of ASAs) were affected by the factors. The factors were selected based on particular statistical tests. The intra-class correlation coefficients (ICC) as a test-retest reliability index for repetitive measurements of force values for each axis were found to be more than 0.9 (p <.001) in all conditions. Mauchly's sphericity test was used to confirm the assumptions of sphericity, and the Greenhouse-Geisser correction was used when the sphericity assumption was rejected. For the post-hoc test, multiple pairwise comparisons with Bonferroni correction was conducted. All statistical significance

level was set at $p < 0.05$.

6.3. Results

6.3.1. Performance indices

6.3.1.1. Angle and force error at t_0

In the angle error of the bow (experimental frame) according to 0° at t_0 and average F_{TOT} error according to the F_{REF} (Mean FEt_0), there was no statistically significant difference between the two release types. However, in SD of FE t_0, the value of RT was significantly higher than that of ST. A repeated measure ANOVA supported these findings with factors *Type of release* (two levels: ST, RT), which showed significant main effects ($F_{[1,7]} = 6.59$, $p = 0.037$, $\eta p^2 = 0.48$)

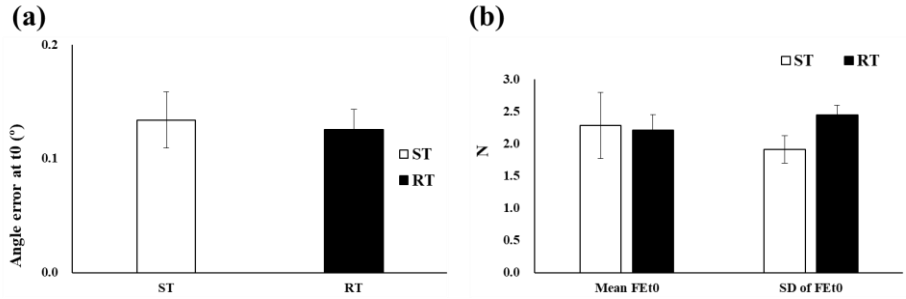

Figure 6-2. (a) angle error at t_0 according to 0° at t_0, and mean and (b) standard deviation (SD) of force error et t_0 according to the F_{REF} (mean FEt_0 and SD of FEt_0). Values are means ± standard errors across the subjects.

6.3.1.2. Indices of accuracy and precision (ACI_{NORM}, PRI_{NORM})

The indices of precision (PRI_{NORM}) was larger in the RT condition than in

the ST condition. (i.e., in ST condition shows the better precision for the performance). These findings were supported by repeated measure ANOVA with factor *Type of release* on PRI ($F_{[1, 7]} = 12.28$, $p = 0.010$, $\eta p^2 = 0.64$).

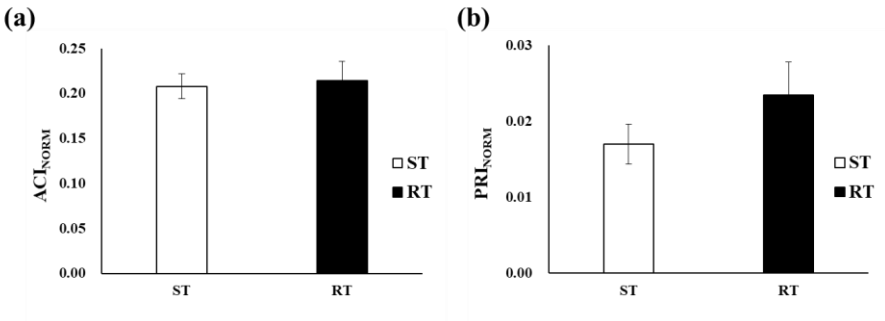

Figure 6-3. Accuracy index (ACI_{NORM}, a), the mean displacement of the location of the virtual projectile from the center of the virtual target for each finger combination (IM, IMR, and IMRL), and precision index (PRI_{NORM}, b), the mean distance of the location of the virtual projectile in a given trial from the mean location of the virtual projectile in previous trials. The data from the eight participants are presented as means and standard errors.

6.3.1.3. Release time

The participants performed 20 repetitive trials for the multi-finger force production and release task for each DOF condition. Generally, there was no significant difference in the average release time across the trials between the conditions.

6.3.2. Synergy indices

6.3.2.1. Synergy indices in force space

We quantified the indices of force stabilization synergies for the upper and lower hierarchies ($UH\_\Delta V_F$, $LH\_\Delta V_F$) during the steady-state force production. In

general, the ΔV_F value did not show a difference according to each condition. These findings were supported by a two-way repeated measure ANOVA on ΔV_F setting factors as *Type of release* and *Axis*. The results showed significant main effects of *Axis* ($F_{[2, 14]} = 48.48$, $p < 0.001$, $\eta p^2 = 0.87$ for UH; $F_{[2, 14]} = 48.48$, $p < 0.001$, $\eta p^2 = 0.87$ for UH) without significant *Type of release* × *Axis*.

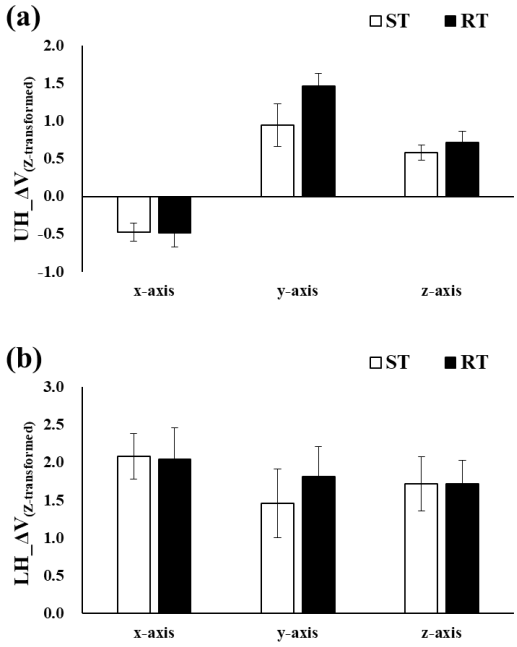

Figure 6-4. Z-transformed synergy indices with respect to F_{TOT} stabilization, ΔV_F, for each hierarchy on the *x*-, *y*-, and *z*-axes of ST (white bars), and RT (black bars) condition. Values are means ± standard errors across the subjects.

6.3.2.2. Synergy indices in M-mode space

We computed the COP of GRF stabilization synergies in M-mode space ($\Delta V_{M\text{-}mode}$) during the steady-state force production. The $\Delta V_{M\text{-}mode}$ was shown to be positive under both conditions. However, the $\Delta V_{M\text{-}mode}$ value did not show a difference according to each condition.

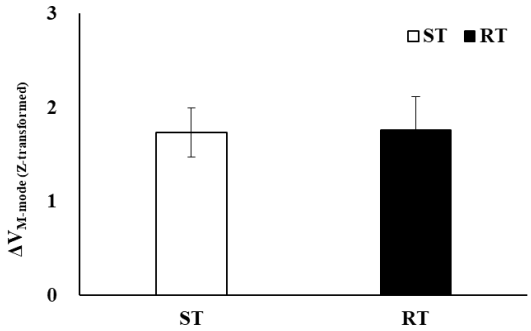

Figure 6-5. Z-transformed synergy indices with respect to COP of GRF stabilization in $\Delta V_{M\text{-}mode}$ space during the SS phase were presented for the ST (white bars), and RT (black bars) condition. Values are means ± standard errors across the subjects.

6.3.3. Time and magnitude of ASA

In the case of the ΔV_F of upper hierarchy (thick solid lines), it can be seen that the change of value occurs before the t_0, and in particular, it can be seen that the change is faster under the ST condition (solid black line).

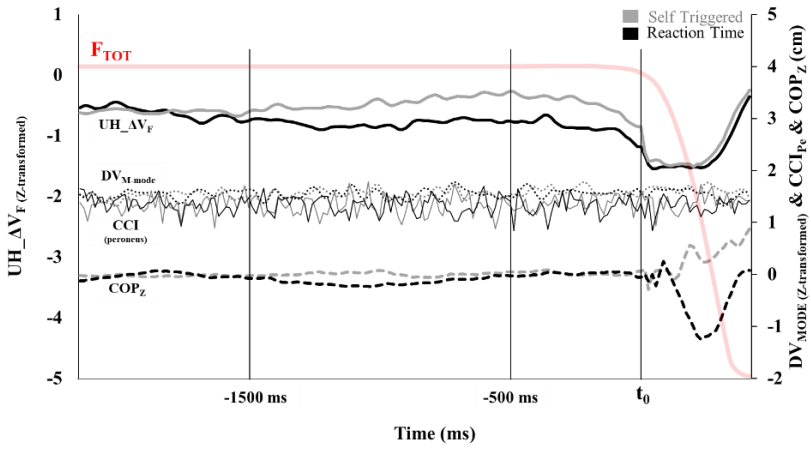

Figure 6-6. The total force (F_{TOT}, red line), ΔV_F of upper hierarchy (thick solid lines), *z*-axis component of COP (dashed lines), $\Delta V_{M\text{-}mode}$ (thin dashed lines), and co-contraction index (CCI) of right and left peroneus muscles (thin solid lines) were presented in time-series. Average values across subjects is presented. In the case of UH_ΔV value, it should be noted that the sign is reversed in consideration of the opposite direction of the force of both hands.

6.3.3.1. Time of ASA in force space

The time of ASA according to t_0 (t_{ASA}) of ST condition was relatively longer than RT condition in upper hierarchy (UH). However, in lower hierarchy (LH), t_{ASA} was relatively short and there was no statistically significant difference between the two conditions. A repeated measure ANOVA supported these findings with factors *Type of release* (two levels: ST, RT), which showed significant main effects ($F_{[1,7]}$ = 22.02, p = 0.002, ηp^2 = 0.76) on UH.

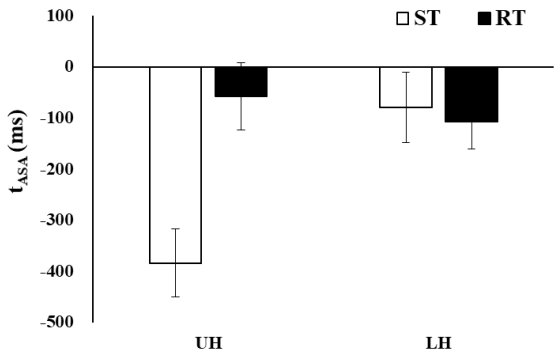

Figure 6-7. The time of ASA according to t_0 (t_{ASA}) for each hierarchy (UH and LH) of ST (white bars), and RT (black bars) condition. Values are means ± standard errors across the subjects.

6.3.3.2. Magnitude of ASA in force space

We computed also the magnitude of ASA for each hierarchy and each axis. However, the magnitude of ASA value did not show a difference according to each condition.

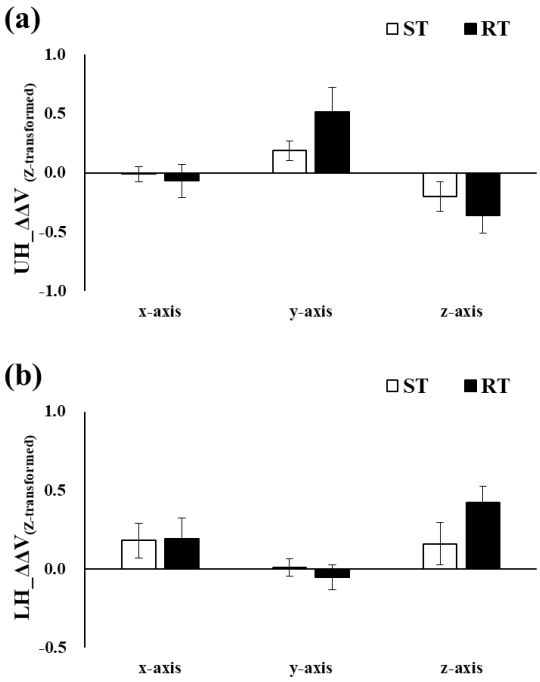

Figure 6-8. The magnitude of ASA according to t_0 for each hierarchy (UH and LH) of ST (white bars), and RT (black bars) condition. Values are means ± standard errors across the subjects.

6.4. Discussion

The purpose of this study was to understand the anticipatory control mechanism of synergy observed hierarchically in the nervous system and to determine the effect of this anticipatory control mechanism on the performance of the task. Archery shooting operations determine performance through the creation and maintenance of accurate and stable forces and consistent release (Leroyer et al., 1993; Martin et al., 1990; Nishizono et al., 1987). To do so, it is also important to coordinate the muscles that keep the body system stable from external forces. In this study, including two hierarchies of the synergy stabilizing the task, and synergy of

muscle level stabilizing the body posture on the analysis. Therefore, we tried to verify the following hypothesis by reproducing the shooting operation of archery as an experimental situation. First, there will be synergies of each hierarchy during aiming (bimanual synergy of both hands, the multi-finger synergy of shooting hands, and muscle synergy of each involved muscle). Second, the anticipatory control mechanism (APA and ASA) will be different depending on the release type. Third, the performance indices will be different depending on the anticipatory condition.

The results showed that the negative covariation pattern (positive synergy index) was observed at the bimanual level (upper hierarchy) and multi-finger level. However, the bimanual level mediolateral direction (*x*-axis) showed a positive covariation pattern (negative synergy index). Anteroposterior direction (*z*-axis) is also considered to be positive covariation in the magnitude of the force, considering that the direction of the two-hand force is reversed. This characteristic reflects the characteristics of the task of stabilizing the position and orientation of the experimental frame, which is similar to the previous chapter (Chapter 5). On the other hand, the muscles involved in maintaining the balance of the body's anteroposterior direction during the task were confirmed to be grouped and controlled. On the other hand, during the task, the muscles involved in maintaining the balance of the body's anteroposterior direction were found to be grouped together. such groups have been documented in recent studies and referred to as M-modes (Danna-dos-Santos, Slomka, Zatsiorsky, & Latash. 2007). According to the results of this study, the synergy index at the muscle mode level also showed a positive value. This suggests that the mechanisms that control each muscle also actively interacted to stabilize the whole body balance (specifically, the center of pressure of the foot).

Synergy can be quantified by the relative magnitude of the variance in the solution space that does not change the performance variable and variance of the space orthogonal to the solution space between redundant elemental variables. In other words, the presence of synergy means that the dispersion of the variance of the solution space is relatively large. ASA refers to a phenomenon in which the variance of the solution space is reduced predictively. So, ASA does not cause visible changes in performance variables (Klous et al., 2011). APA, on the other hand, is a pattern of muscle activity shifting the center of gravity (Massion 1992) and causes changes in performance variables. Previous studies have reported that covariation patterns in muscle mode spaces that stabilize COP occur prior to each individual muscle or muscle mode change. This suggests that the feedforward control process (ASA) associated with postural stabilization is more actively involved than APA (Klous et al., 2011). The study concluded that this requires a reduction in the COP stabilization synergy index (ASA) so that muscles can perform postural adjustment (APA) before movement initiation. We expected that the change in synergy index in muscle mode (M-mode) space would precede the change in co-contraction index (CCI) of both peroneus muscles which contributes to ensuring the stability of the system or COP, and all of these variables were expected to appear before the release. However, in the results, no visible changes were found in variables that could be indicated by the active intervention of the controller, such as M-mode synergy and CCI of peroneus muscle before release. This means that, due to the nature of the task, the amount of effort the controller needs to stabilize the whole body system is very small, and explain that COP stabilization may not be a major consideration in satisfying the tasks of this study.

The independent variable in this study is the release type of finger force. Previous studies have explained that the pattern changes in which each element covariates (synergy) before the force changes (Shim et al., 2005). If the release is required as soon as possible after a visual stimulus (RT condition), the timing of synergy changes can be expected to be later than the self-triggered (ST) condition (Olafsdottir et al., 2005). The results of this study confirmed that the force stabilization synergy index at the bimanual level changes first. Previous studies have described the functional role of anticipatory covariation as a phenomenon that turns off interactions between elemental variables that interfere with the intended change in performance variable (total force) (Olafsdottir et al. 2005). It should be noted that the ASA of the bimanual level is calculated based on the force values of the *z*-axis components, and the magnitude of the force of both hands basically takes the form of positive covariation with each other. The results show that the covariation pattern of the two-hand force, which is changed by the ASA, tends to be more pronounced for the positive covariation tendency. Considering the positive covariation pattern of each normal force in free object control is a natural coupling due to physical constraints, the results of this study are consistent with the description of previous studies. The results showed that this ASA of the bimanual level was more prominent in the self-triggered (ST) condition, which may be related to the results of the task performance. The results show that the reaction time (RT) condition in the force variability is larger than the ST condition at the time of the release of the total force (t_0), and the consistency of task performance (PRI) also showed more consistent under ST conditions. In other words, the results of this study confirmed the anticipatory control mechanism at the bimanual level which is directly related to the performance of the task, which contributed to the consistency of performance.

There are various limitations when comparing this study with actual archery. first of all, the physical assumptions involved in the experiment are different from the actual archery situation. The projected mechanism, shape and weight of the projected object are independent of actual archery, for experimental convenience, we only borrowed the concept of a very small part of archery. In this study, we tried to understand the human motor control mechanism by simplifying the task as much as possible. In order for the results of the study to be more connected with the actual archery performance, the experimental conditions that reflect the physical characteristics of the archery and the game rules should be reflected.

6.5. Conclusion

The purpose of this study was to understand the anticipatory control mechanism of synergy observed hierarchically in the human motor system and to identify the effect of this anticipatory control mechanism on the performance of the task. In conclusion, we verified some of the hypotheses presented in the introduction and confirmed that the anticipatory control mechanism at the task-relevant level contributed to the consistency of task performance.

Chapter 7. General Conclusion

In this study, the archery shooting was partially reproduced by experimenting for accurate and consistent performance through the control of multiple elements in various hierarchies such as both hands and each finger. This study has drawn conclusions through four experimental studies. As a result, increasing kinetic degrees of freedom increases multi-finger synergy, which has a positive effect on improving task performance, and the positive effects of increasing kinetic degrees of freedom can also be extended to hierarchical tasks. Additionally, the anticipatory mechanism of abundant degrees of freedom has a positive effect on the consistency of the task.

In summary, we have confirmed that the human body, which is characterized by hierarchically redundant, contributes to the accuracy and consistency of task performance through active interactions between each element and each hierarchy. We also confirmed that the anticipatory control characteristics of such interactions are a mechanism for the successful performance of the task. In other words, the characteristics of the human motor control system, motor redundancy, is not a computational burden of the central nervous system but a positive contributor to task performance through various solutions.

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국문 초록

인체는 일반적으로 특정 과제를 수행하기 위해 최소한으로 요구되는 것보다 큰 운동역학적 자유도를 가지고 있다. 이를 운동요소과잉이라고 하며, 인체는 여러 계층에 걸쳐 운동요소과잉의 특성을 띠고있다. 때문에 우리의 중추신경계가 과잉 된 자유도를 어떻게 효율적으로 제어할 수 있는지 확인하는 것은 인간운동과학 분야의 주된 연구 주제 중 하나이다. 본 연구의 목적은 요소과잉의 특성을 가진 인간의 다중요소제어기전(시너지)을 실제 과제 수행의 측면에서 이해하는 것이다. 이를 위해 우리는 정확하고 일관된 결과를 지향하는 과제인 양궁의 슈팅 동작을 모방하여 네 차례의 실험 연구를 진행하였다. 그 중 첫번째에서 세번째까지의 연구(chapter 3, 4, 5)를 통해서는 인체 시스템의 계층적 운동요소과잉 특성에 따른 다중요소제어기전이 과제의 정확성 및 일관성에 긍정적으로 기여하는지 확인하였고, 네번째 연구(chapter 6)를 통해서는 인간의 예측적 다중요소제어가 과제의 수행과 어떠한 관련이 있는지를 살펴보았다. 비제어다양체(UCM) 가설에 기반한 분석방법을 통해 각 요소(양손, 각 손가락, 또는 각각의 근육 군) 간의 상호작용 양상(시너지 지수)을 확인하였고, 이를 과제의 정확성 및 일관성과 연관 지어 살펴보았다. 결과적으로, 손가락의 운동역학적 자유도의 증가에 따라 각 요소들 간의 시너지 지수는 증가하였고, 이는 과제 수행의 향상과 관련 있다는 사실을 확인하였다. 이러한 양상은 인체의 여러 계층으로 확장하여 해석할 수 있다는 것 역시 확인하였으며, 인체의 과잉 된 운동요소들의 예측적 제어 기전 역시 과제의 일관성에 기여한다는 것을 확인하였다. 이를 통해 우리는 인간의 운동제어시스템의 특성인 운동요소과잉은 중추신경계에 있어 계산상의 부담이 아니며, 오히려 동작의 다양성을 통해 과제 수행에 기여하는 긍정적 요인이라는 것을 확인하였다.

주요어: 운동요소과잉, 시너지, 예측적 시너지 제어(ASA), 비제어다양체(UCM) 가설, 양궁

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