Relationship between degrees of freedom and adaptability or flexibility in human postural standing

Kentaro Kodama [1], Kazuhiro Yasuda[2], and Hideo Yamagiwa [3]

[1] Kanagawa University, 3-27-1, Rokkakubashi, Kanagawa-ku, Yokohama-shi, Kanagawa, Japan,
kkodama@kanagawa-u.ac.jp

[2] Waseda University, 3-4-1 Okubo, Shinjuku-ku, Tokyo, Japan,
kazuhiro-yasuda@aoni.waseda.jp

[3] Tokyo Metropolitan Tobu Medical Center, 3-3-25, Shinsuna, Koto-ku, Tokyo, Japan,
somatolearning@gmail.com

Abstract. This study aimed to investigate the direct relationship between the joint degrees of freedom (DoF) of human movement system and its postural dynamics in terms of adaptability/flexibility. In our pilot experiment we fixed the join DoF (knee and ankle) to constrain the functional DoFs (one for knee, two for ankle). Young healthy participants were required to maintain single-leg standing task with their dominant leg fixed. The center of pressure (COP) trajectory data were measured and analyzed by linear and nonlinear methods to assess static and dynamic property of their postural dynamics. As a result of comparing across conditions (normal no-fixation, ankle and knee fixation condition), static measure (COP trajectory length) did not significantly differ across conditions. However, dynamic measures (the fractal scaling exponent and sample entropy) significantly differed. The ankle joint fixation affected the scaling behavior (weakening the under-diffusive postural control process), and sample entropy decline (losing efficiency of postural control) in the ML direction. These results seemed to agree with the notion of the loss of complexity framework.

Keywords: loss of complexity, freezing degrees of freedom, single-leg standing, fractal analysis, entropy analysis

1 Introduction

1.1 Adaptability/flexibility as an embodied skill

Adaptability and flexibility can be considered unique abilities of human beings or living organisms in contrast to traditional robots or artificial intelligence (AI). These abilities enable living systems to adapt flexibly to their environment which can vary dynamically. In the AI research field, such a dynamic ability to respond to dynamic situations and behave flexibly is considered an essential feature of *intelligence* (Suwa, 2013). It is also related to another important concept *embodiment*. The living body consists of perception and action systems that have dynamic real-time interactions with their environment (Gibson, 1966). Authors have called such an embodied skill *dynamic embodied adaptability* and it is supposed to be a characteristic property of living systems, which differ from traditional robots or AI (Kodama, Kikuchi, & Yamagiwa, 2017). Although these artificial systems are good at repeating the same movement or process in the same way, living systems are not; however, they perform the same task in a variety of the different ways. Such variability is an important feature of human skilled performance particularly in terms of adaptable/flexible behavior (Bernstein, 1967; Kudo & Ohtsuki, 2008).

For example, Nonaka (2013) investigated skilled coordinated behavior of an exceptional tetraplegic individual who has practiced Japanese calligraphy with a mouth-held brush (Nonaka, 2013). The author showed evidence that joint configuration variances at different phases of writing were structured so as to maintain some important task variables across different realizations of the writing task; moreover compensatory coupling between joint variables contributed to the observed structure of joint configuration variance (Nonaka, 2013). In another study, he and his colleague compared flexible bead-making behavior of bead craftsmen with different skill levels (Nonaka & Bril, 2014). As a result, they found that the highly skilled craftsman had rich flexibility and exquisite context sensitivity as well as the largest interstroke variability in the coordination of movement (Nonaka & Bril, 2012, 2014). Ito and her colleagues examined the role of postural control in a skilled task that requires perceptual-motor coordination of expert *Kendama* players (Ito, Mishima, & Sasaki, 2011). They revealed the importance of flexibility of knee movement to support dynamical coordination between body movement and the moving ball and the stability of the strong coupling of the head and the ball (Ito et al., 2011). Then how can adaptability/flexibility be realized and how can variability of observed data be explained?

1.2 Degree of freedom and complex systems

In human movement science and skill science research fields, it is said that the functional degrees of freedom (DoF) can provide the human movement system with the foundation of adaptive/flexible or skilled behavior. The human body has many multifarious DoFs, from the microscopic cell level to macroscopic joint level (Bernstein, 1967; Turvey, 1990). The DoF problem suggested that the large number of controllable DoFs poses a computational burden to the central nervous system, if we assume a computational model (Turvey, 1990). This indicates the difficulty of the unidirectional top-down motor control model using computer metaphor. Bernstein, who proposed the DoF problem, supposed that each component (DoF) is coordinated and coupled with other components to organize a functional unit (*synergy*) rather than being controlled separately (Bernstein, 1967). Bernstein attempted to solve the DoF problem with the idea of synergy. Such coupled components are not organized in non-directional or random ways, but in sensitive and flexible way to achieve a specific task in a specific situation/environment (Bernstein, 1996).

Although the DoF problem is actually a problem from the viewpoint of the computational model (top-down motor control model), it is also possible to consider redundant DoFs as a benefit to enable movement systems to behave adaptably/flexibly. The human body has an intrinsic fluctuation derived from a physiological mechanism and is exposed to external perturbation from its environment or own body movement. However, if the system has redundant DoFs and an ability to freeze and release them quickly, it might realize stable behavior in an adaptive/flexible way against intrinsic fluctuation or external perturbation (Kodama & Aoyama, 2017).

After Bernstein's proposal of the DoF problem and the idea of synergy, the self-organization theory (Haken, 1978; Nicolis & Prigogine, 1977) was applied to human movement studies to understand emergent properties of a human movement system. It is called the *dynamical systems approach* (DSA) and has been widely applied to human movement science areas. Compared to the traditional approach to motor behavior assuming internal computation, DSA focuses more on interactions between the body (including brain), environment, and task (Davids, Glazier, Araújo, & Bartlett, 2003). While the traditional top-down motor control model supposes a dominant central system (i.e., brain) and focuses on its component, DSA focuses on the interaction among system's component (Van Orden, Holden, & Turvey, 2003). Complex systems consist of a large number of interacting components (DoF); the emergent behavior of the system is self-organized and can be difficult to anticipate from dynamics of the individual components (Boccara, 2003). Their emergent behavior does not result from the existence of a central controller like brain (Boccara, 2003).

1.3 Loss of complexity hypothesis

The perspective of the self-organizing theory provides new insight and a useful framework for not only human movement science and skill science, but also the clinical and therapeutic research fields. The *loss of complexity hypothesis* is a broad theoretical perspective applied widely to physiological and behavioral processes (Lipsitz & Goldberger, 1992). According to the hypothesis, the age- and/or disease-related changing process can be defined by a progressive loss of complexity within the dynamics of physiologic outputs (e.g., physiological and behavioral data) (Manor & Lipsitz, 2013). In other words, loss of complexity leads to an impaired ability to adapt to stressors or perturbation (Lipsitz & Goldberger, 1992). It is supposed to be due to a loss or impairment of functional components, and/or altered nonlinear coupling between these components (Lipsitz & Goldberger, 1992). Thus, the hypothesis assumes that a system's adaptive/flexible function relates to its complexity and is observed in the dynamics of the system's output behavior (e.g., physiological and behavioral times series data). Moreover, these dynamics are characterized by the presence of fractal scaling or the amount of regularity/predictability in the dynamics (Lipsitz & Goldberger, 1992; Stergiou, 2016).

For postural balance studies, the loss of complexity hypothesis has been applied and the center of pressure (COP) fluctuation is supposed to relate to the adaptive/flexible function of the postural system. For example, the postural dynamics of healthy young and healthy elderly people have high complexity than that of elderly people who have a history of falls (Costa et al., 2007). Parkinson's disease patients also show lower flexibility in terms of deterministic structure of the COP dynamics than healthy participants (Schmit et al., 2006). Sensory impairments contributed to a decreased COP complexity, which reflected a reduced adaptive capacity of the postural control system (Manor et al., 2010).

Those postural balance studies applied nonlinear analysis methods like *fractal analysis* and *entropy analysis* to COP time series data. Fractal analysis is a time series analysis that obtains a dynamic measure. It can evaluate the temporal correlation of a time series (Brown & Liebovitch, 2010). Such a property is called a fractal property or $1/f$ noise and indicates that fluctuations in the time series extend across many time scales (Eke, Herman, Kocsis, & Kozak, 2002). Such relative independence of the underlying processes at different time scales suggests that $1/f$ noise renders the system more stable and more adaptive to internal and external perturbations (Delignières, Torre, & Lemoine, 2005). Thus, fractal property is considered a dynamic measure and is associated with health/pathology (Lipsitz & Goldberger, 1992) and flexibility/adaptability (Hausdorff, 2009). To assess the complexity of the system, dynamic measure based the idea of *entropy* derived from information theory has been also applied to biological and physiological data. Entropy refers to the rate of information generation by a system. While repeating systems generate less new information, systems with varying complexly generate new (non-redundant) information when the system visits new states. Generally, high entropy means relatively irregular and complex variability. In contrast, low entropy means regular and predictable behavior. According to the loss of complexity hypothesis, healthy systems are characterized by an irregular and complex variability, whereas disease or aging is associated with regularity/predictability and less complexity (Goldberger et al., 2002; Pincus, 1991).

It is supposed that the loss of complexity relates to a decline in the capability to reorganize the interactions between its components (its functional DoF) to adjust the degree of unpredictability of behavioral fluctuations to meet task demands (Sleimen-malkoun, Temprado, & Hong, 2014). Aging and/or disease are involved in change in coupling between components (DoFs) and the decrease in interaction between them. In other words, systems with less interaction between their components and few functional DoFs tend to behave regularly and their dynamics lose dimensionality or complexity (Sleimen-malkoun et al., 2014). However, most previous studies have investigated the relationship between DoF and system dynamics by comparing particular populations such as elderly/impaired people with healthy young people. In these cases, it is difficult to reveal the direct relationship between the DoF and system dynamics because other factors derived from aging and/or disease cannot be ignored.

1.4 Our research aims

As an exploratory investigation, our pilot study manipulated the DoF of a human movement system (i.e., joint) as an independent variable, and compared different DoF conditions within subjects. We fixed and constrained the ankle joint (two DoFs) and knee joint (one DoF) of the dominant leg and required young healthy participants to perform single-leg standing task by their dominant legs; this was compared to the no-fixation normal condition. The COP trajectory data were measured and analyzed by linear and nonlinear methods to assess a static and dynamic properties of the postural dynamics. Then, the direct relationship between the DoF and COP dynamics was investigated. Such an investigation may lead to deeper understanding of their relationship and provide an experimental evidence of the loss of complexity hypothesis.

2 Method

2.1 Participants

Six healthy male participants (average = 23.50 (SD=4.68) years, all right-handed) were recruited to join the experiment. The experimental procedures were approved by the research ethics committee of Kanagawa University, where the experiment was conducted. Each participant provided informed consent for participation in this study.

2.2

Joint fixation equipment (REAQER ankle supporter, REAQER knee supporter, **Fig.1**) were used to fix the ankle and knee joints. The center of pressure (COP) trajectories were measured using a force plate (Leptrino CFP600YA302US, sample rate = 200 Hz). To process and analyze COP data, MATLAB (R2017b, MathWorks) and RStudio (Version 1.1.423) were used to process and analyze the COP data.

2.3 Procedure

In the current pilot experiment, three conditions were compared, namely, the normal condition (no joint fixation), ankle condition (ankle joint fixation), and knee condition (knee joint fixation) as shown in **Fig.1**. Under the joint fixation conditions, each joint of the dominant leg (i.e., right leg) of each participant was fixed using the equipment. Each participant was asked to maintain single-leg standing with their dominant leg for 35-s. After conducting the normal condition task first as a baseline condition, the ankle and knee condition tasks were counterbalanced between the participants. Under each condition, they were required to repeat a 35-s trial four times with 30-s interval between trials, and with 3-min rest between conditions.

Fig. 1. Experimental conditions and joint fixation equipment (Left: Normal condition, Middle: Ankle condition, Right: Knee condition).

2.4 Data Analysis

After measuring the COP trajectory data, we removed the initial 5-s data and analyzed the remaining 30-s of time series data of the COP in the mediolateral (ML) and anteroposterior (AP) directions. Before performing the following time series analyses, all COP data were smoothed by a 10-Hz low-pass filter (4^{th} order Butterworth filter).

To assess postural stability, the COP trajectory length was calculated and regarded as a static measure (Horak, 1989; Shumway-Cook & Woollacott, 2013). This measure defines shorter trajectory length as less movement (less postural sway) and it means more stable posture. In this sense, we interpret this as a static measure.

By contrast, to evaluate dynamic postural stability, we also applied nonlinear time series analyses, *detrended fluctuation analysis* (DFA; Peng et al., 1994) and *sample entropy* (SampEn; Richman, R., & Moorman, 2000). DFA is a fractal analysis for nonlinear time series data, and has been used to assess a system's adaptability/flexibility (Hausdorff, 2009) in terms of temporal correlation in time series data (Brown & Liebovitch, 2010). DFA calculates the scaling exponent α as the slope of the log-log plot of fluctuation vs. time scale. A linear relationship on a log-log plot indicates the presence of scaling. The DFA scaling exponent α is interpreted as an estimation of the Hurst exponent H, and is related to H as follows (Delignières, Torre, & Bernard, 2011): if $0 < \alpha < 1$, then $H=\alpha$; if $1 < \alpha < 2$, then $H=\alpha-1$. H can be interpreted for the time series as follows: if $0 < H < 0.5$, the time series is anti-persistent/under-diffusive; if $H = 0.5$, it is uncorrelated (*white noise*); if $0.5 < H < 1$, it is persistent/over-diffusive; if $H = 1$, it is considered $1/f$ *noise* (Marmelat, Torre, & Delignières, 2012). *Sample entropy* analysis is a method with which to quantify the complexity or irregularity of a time series (Richman et al., 2000). Sample entropy (SampEn) indexes the (ir)regularity of a time series and is used to analyze the dynamics of complex systems. While a smaller sample entropy means greater regularity, a larger sample entropy indicates relatively irregular or complex dynamics. For a given embedding dimension m, tolerance r, and number of data points N, SampEn is the negative logarithm of the probability that if two sets of simultaneous data points of length m have distance $< r$ then two sets of simultaneous data points of length $m+1$ also have distance $<r$ (Stergiou, 2016). DFA was performed using the R package '*nonlinearTseries*' (Constantinoet al., 2015). SampEn was performed using the R package ' *pracma*' (Borchers, 2018) with input parameters, embedding dimension $m=3$ and a ratio of standard deviation of the data of $r=0.2$.

3 Result and Discussion

3.1 COP Trajectory Length

Fig. 2 shows the mean COP trajectory length for each condition (left: normal condition; center: ankle condition; right: the knee condition; error bar: standard deviation). The mean value was 1393.61 (SD=228.82) [mm] in the normal condition, 1507.60 (SD=210.93) [mm] in the ankle condition, and 1471.48 (SD=350.43) [mm] in the knee condition. The results seem to indicate that postural sway is the smallest in the normal condition, which is the largest DoF condition. However, the result of one-way ANOVA revealed no significant differences between the conditions ($F(2, 10)=0.995$, $p=0.404$, *N.S.*). This implies that the joint fixation did not affect the static measure, which is the COP trajectory length (i.e., how much posture fluctuate) in the case of our pilot study (N=6).

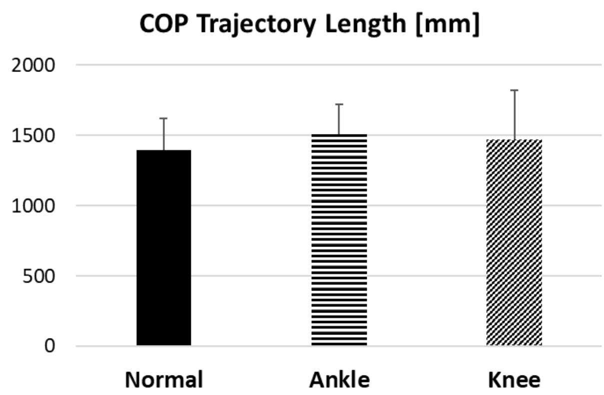

Fig. 2 COP trajectory length [mm] (Left: Normal condition; Center: Ankle condition; Right: Knee condition).

3.2 DFA Scaling Exponent α

Fig. 3 displays the mean DFA scaling exponent for each condition in the ML and AP directions, respectively (left: normal condition; center: ankle condition; right: the knee condition; error bar: standard deviation). In the ML direction, the mean value was 1.17 (SD=0.07) in the normal condition, 1.25 (SD=0.05) in the ankle condition, and 1.18 (SD=0.06) in the knee condition. In the AP direction, the mean value was 1.30 (SD=0.09) in the normal condition, 1.31 (SD=0.09) in the ankle condition, and 1.30 (SD=0.10) in the knee condition. To compare these values statistically, one-way ANOVA was conducted for each scaling exponent α of both the ML and AP directions. The results show that we found the significant main effect on the scaling exponent α only in the ML direction ($F(2, 10)=0.011$, $p<0.05$). Because of multiple comparisons (Ryan's method), significant differences were found between the ankle and normal conditions ($t(5)=2.833$, $p<0.05$), and between the ankle and knee conditions ($t(5)=2.415$, $p<0.05$). These results indicate that the scaling exponent α was larger in the ankle condition than in the other conditions in the ML direction. In contrast, there was no significant main effect in the AP direction ($F(2, 10)=0.081$, $p=0.922$, *N.S.*).

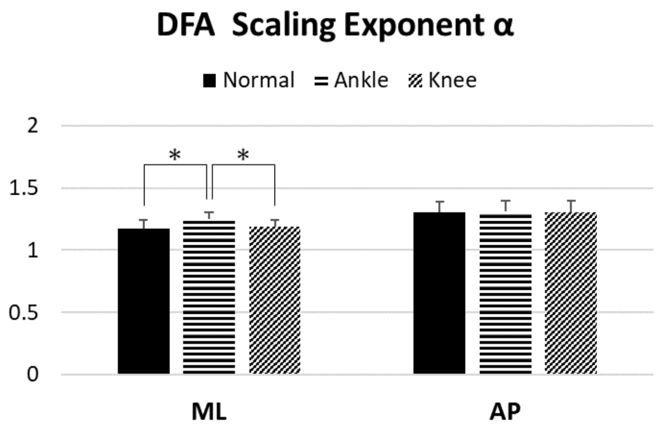

Fig. 2 DFA scaling exponent α (Left side *x*-axis ML direction, Right side: *y*-axis AP direction, in each side, Left: Normal condition, Middle: Ankle condition, Right: Knee condition).

The DFA scaling exponent is interpreted as follows: if $\alpha=1$, then the time series has persistent long-range correlations (i.e., $1/f$ pink noise); if $\alpha=1.5$, indicates Brownian motion. For $1<\alpha<1.5$, the time series has correlation, but lose fractality and ceases to be a power-law relation (Peng, Havlin, Stanley, & Goldberger, 1995). In the current data, the DFA scaling exponents were ranged between 1 and 1.5. Within this range, the scaling exponent α is related to the Hurst exponent H as $H=\alpha-1$. This implies that an increasing trend in the past is likely to be followed by a decreasing trend, and an anti-persistent correlation/under-diffusive process (Marmelat et al., 2012). In terms of fractality, if $0.75<\alpha<1.25$, then the time series has long-range correlation and indicates $1/f$ pink noise (Marmelat et al., 2012). Comparing our results across conditions, α was higher in the ankle condition than other two conditions in the ML direction. This means that the under-diffusive process that regulates single-leg standing posture in the ML direction weakened when the ankle joint was fixed. In other words, adaptability/flexibility was higher in the normal and knee conditions than in the ankle condition because the scaling exponent in the normal and knee conditions were ranged between $0.75<\alpha<1.25$. If so, the ankle joint fixation might cause loss of adaptability/flexibility.

3.3 Sample Entropy

Fig. 4 represents the mean SampEn for each condition in the ML and AP directions respectively (left: normal condition; center: ankle condition; right: the knee condition; error bar: standard deviation). In the ML direction, the mean value was 0.117 (SD=0.023) in the normal condition, 0.095 (SD=0.018) in the ankle condition, and 0.116 (SD=0.025) in the knee condition. In the AP direction, the mean value was 0.073 (SD=0.026) in the normal condition, 0.076 (SD=0.026) in the ankle condition, and 0.074 (SD=0.026) in the knee condition. To compare these values statistically, one-way ANOVA was conducted for each SampEn of both the ML and AP directions. The results show that we found the significant main effect on SampEn only in the ML direction ($F(2, 10)=4.295$, $p<0.05$). Because of multiple comparisons (Ryan's method), significant differences were found between the ankle and normal conditions ($t(5)=2.616$, $p<0.05$), and between the ankle and knee conditions ($t(5)=2.453$, $p<0.05$). These results indicate that SampEn was larger in the ankle condition than in the other conditions in the ML direction. In contrast, there was no significant main effect in the AP direction ($F(2, 10)=0.071$, $p=0.931$, *N.S.*).

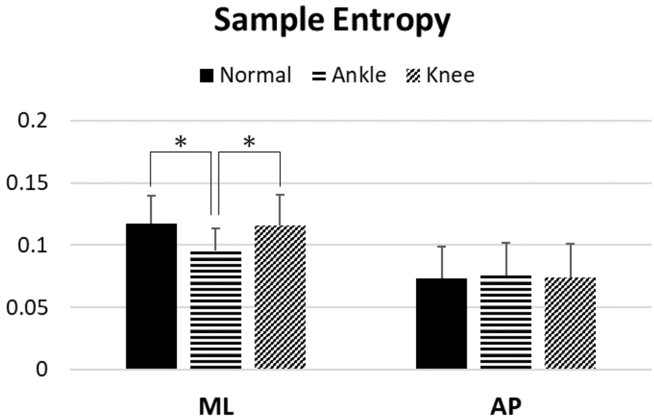

Fig. 3 Sample Entropy (Left side *x*-axis ML direction, Right side: *y*-axis AP direction, in each side, Left: Normal condition, Middle: Ankle condition, Right: Knee condition).

A high SampEn indicates relatively low regularity or complexity, while low SampEn means relatively high regularity or predictability. In the current data, postural sway was more regular in the ML direction in the ankle condition than the other two conditions. The result suggests that low SampEn (more regular postural sway) in the ankle condition was interpreted as an increase in the effectiveness of postural control in the ML direction in terms of amount of attention or cognitive involvement (Donker, Roerdink, Greven, & Beek, 2007). Some previous studies argued that postural sway regularity is positively correlated with the degree of cognitive involvement in postural control (Donker et al., 2007; Roerdink et al., 2006). Actually, some participants reported that it was more difficult to perform the single-leg standing task in the ankle condition than in other two conditions. We guess that such a difficulty leaded to more attention to postural control and more regular postural sway in the ankle condition.

3.4 General Discussion

COP trajectory length can be interpreted as a static measure because it indicates how much postural sway is observed and it is defined as less movement or more stable sway. In the current pilot experiment, we could not find any significant differences between the conditions in terms of the quantity of postural sway. This means that joint fixation did not affect the static balancing ability of single-leg standing. In contrast, the DFA scaling exponent α and SampEn can be considered dynamic measures because they quantify how the posture fluctuated in terms of temporal correlation or temporal pattern complexity of the time series data. Our results suggest that postural sway during the single-leg standing task had a weaker under-diffusive process and less irregular/complex fluctuation in the ML direction in the ankle condition than in the other two conditions.

The single-leg standing task requires postural control based on foot function using ankle joint movement (King & Zatsiorsky, 2002). The ankle joint fixation seemed to constrain the mobility of the foot movement and postural control in the ML direction, whereas the knee joint fixation did not affect the postural dynamics because the knee joint has only one DoF (flexion-extension) and is not involved in postural control in the ML direction. In terms of functional DoF, the knee joint has one DoF and the ankle joint has two DoFs, therefore the results of fractal analysis show that the ankle joint fixation might cause less adaptability/flexibility. This notion is reasonable from the viewpoint of the loss of complexity hypothesis (Sleimen-malkoun et al., 2014). On the other hand, the results of entropy analysis suggest that the ankle joint fixation might cause relatively regular postural sway (low sample entropy); in other words, it might evoke a loss of complexity in the postural dynamics in the ML direction. This notion also seems to agree with the loss of complexity hypothesis (Sleimen-malkoun et al., 2014).

3.5 Future directions

The present article reports only the results of the pilot experiment (N=6). We should collect more data and confirm whether a similar tendency can be found in the future. In addition, we also plan to investigate not only single-leg standing with the dominant leg, but also other balancing tasks. In terms of data analysis, other methods should be conducted to quantify adaptability/flexibility, complexity, and dimensionality (Bravi, Longtin, Seely, & Ca, 2011; Cavanaugh, Guskiewicz, & Stergiou, 2005; Hidaka & Kashyap, 2013), and associate them with empirical data of previous studies.

As discussed, our results should be explained from kinematic or biomechanical perspective in more detail to understand the relationship between the functional DoF (and its fixation) and the system dynamics in terms of complexity and adaptability/flexibility. Further experimental studies regarding the effects of the freeze and release of DoF on the static and dynamic properties of system dynamics may lead to a deeper understanding the direct relationship between them and to obtaining empirical evidence on the loss of complexity hypothesis. We also expect that such experimental strategies can provide more applied research on not only the clinical assessment of the fall risk of elderly/impaired people, but also practical evaluation of sports skills or dexterous performances of athletes with further validity of quantification and evaluation using various data analytical methods.

4 Conclusion

This article reported the results of our pilot experiment to investigate the direct relationship between the joint DoF of the human movement system and its postural dynamics in terms of adaptability/flexibility. In the experiment we manipulated the join DoFs (knee and ankle) with joint fixation equipment. Young healthy participants were required to maintain single-leg standing with their dominant leg fixed. The COP time series data were measured and analyzed by linear and nonlinear methods to assess the static and dynamic properties of their postural dynamics. The results of comparing across conditions (normal no-fixation, and ankle and knee fixation condition) show that the static measure (COP trajectory length) did not significantly differ across conditions; however, the dynamic measures (DFA scaling exponent and sample entropy) differed significantly. The ankle joint fixation (two DoFs constrained condition) affected the scaling behavior leading to weakening of the under-diffusive postural control process, and a sample entropy decline which indicated the losing efficiency of postural control requiring an amount of attention (cognitive involvement). These results of dynamic measures seem to agree with the previous studies' insight within the loss of complexity framework that suggests that less functional DoF might lead to loss of complexity or adaptability/flexibility of the system behavior.

Reference

Bernstein, N. A. (1967). *The Co-ordination and regulation of movements*. Pergamon Press Ltd.

Bernstein, N. A. (1996). *Dexterity and Its Development*. Psychology Press.

Boccara, N. (2003). *Modeling complex systems* (1st ed.). Springer.

Borchers, H. W. (2018). Package “pracma.” Retrieved from https://cran.r-project.org/web/packages/pracma/pracma.pdf

Bravi, A., Longtin, A., Seely, A. J., & Ca, B. (2011). Review and classification of variability analysis techniques with clinical applications. *BioMedical Engineering OnLine*, *10*(October), 90. https://doi.org/10.1186/1475-925X-10-90

Brown, C. T., & Liebovitch, L. S. (2010). *Fractal analysis*. SAGE PublicationsSage UK: London, England. Retrieved from https://uk.sagepub.com/en-gb/asi/fractal-analysis/book233383

Cavanaugh, J. T., Guskiewicz, K. M., & Stergiou, N. (2005). A nonlinear dynamic approach for evaluating postural control: new directions for the management of sport-related cerebral concussion. *Sports Med*, *35*(11), 935–950. https://doi.org/0112-1642/05/011-0935

Constantino, M., Garcia, A., Constantino, A., & Sawitzki, G. (2015). Package “nonlinearTseries.” Retrieved from https://cran.r-project.org/web/packages/nonlinearTseries/nonlinearTseries.pdf

Costa, M., Priplata, A. A., Lipsitz, L. A., Wu, Z., Huang, N. E., Goldberger, A. L., & Peng, C.-K. (2007). Noise and poise: Enhancement of postural complexity in the elderly with a stochastic-resonance-based therapy. *Europhysics Letters*, *77*, 68008. https://doi.org/10.1209/0295-5075/77/68008

Davids, K., Glazier, P., Araújo, D., & Bartlett, R. (2003). Movement systems as dynamical systems: The functional role of variability and its implications for sports medicine. *Sports Medicine*, *33*(4), 245–260. https://doi.org/10.2165/00007256-200333040-00001

Delignières, D., Torre, K., & Bernard, P.-L. (2011). Transition from persistent to anti-persistent correlations in postural sway indicates velocity-based control. *PLoS Computational Biology*, *7*(2), e1001089. https://doi.org/10.1371/journal.pcbi.1001089

Delignières, D., Torre, K., & Lemoine, L. (2005). Methodological issues in the application of monofractal analyses in psychological and behavioral research. *Nonlinear Dynamics, Psychology, and Life Sciences*, *9*(4), 451–477. https://doi.org/10.1093/beheco/aru014

Donker, S. F., Roerdink, M., Greven, A. J., & Beek, P. J. (2007). Regularity of center-of-pressure trajectories depends on the amount of attention invested in postural control. *Experimental Brain Research*, *181*(1), 1–11. https://doi.org/10.1007/s00221-007-0905-4

Eke, A., Herman, P., Kocsis, L., & Kozak, L. R. (2002). Fractal characterization of complexity in temporal physiological signals. *Physiological Measurement*, *23*(1), R1–R38. https://doi.org/10.1088/0967-3334/23/1/201

Gibson, J. J. (1966). *The senses considered as perceptual systems.* Praeger.

Goldberger, A. L., Amaral, L. A. N., Hausdorff, J. M., Ivanov, P. C., Peng, C., & Stanley, H. E. (2002). Fractal dynamics in physiology: Alterations with disease and aging. *Proceedings of the National Academy of Sciences*, *99*(Supplement 1), 2466–2472. https://doi.org/10.1073/pnas.012579499

Haken, H. (1978). *Synergetics: an introduction : nonequilibrium phase transitions and self-organization in physics, chemistry and biology*. Springer-Verlag. Retrieved from https://books.google.co.jp/books/about/Synergetics.html?id=z9PuAAAAMAAJ&pgis=1

Hausdorff, J. M. (2009). Gait dynamics in Parkinson’s disease: Common and distinct behavior among stride length, gait variability, and fractal-like scaling. *Chaos*, *19*(2). https://doi.org/10.1063/1.3147408

Hidaka, S., & Kashyap, N. (2013). On the Estimation of Pointwise Dimension. Retrieved from http://arxiv.org/abs/1312.2298

Horak, F. (1989). Components of postural dyscontrol in the elderly : A review. *Neurobiology of Aging*, *10*(6), 727–738. https://doi.org/10.1016/0197-4580(89)90010-9

Ito, M., Mishima, H., & Sasaki, M. (2011). The Dynamical Stability of Visual Coupling and Knee Flexibility in Skilled Kendama Players, 308–332. https://doi.org/10.1080/10407413.2011.617669

King, D. L., & Zatsiorsky, V. M. (2002). Periods of extreme ankle displacement during one-legged standing. *Gait & Posture*, *15*(2), 172–179. https://doi.org/10.1016/S0966-6362(01)00189-8

Kodama, K., & Aoyama, K. (2017). Foundation of Ecological Approach. In *Rihabilitation based on Perception*. CBR.

Kodama, K., Kikuchi, Y., & Yamagiwa, H. (2017). Whole-body coordination skill for dynamic balancing on a slackline. In *JSAI International Symposium on Artificial Intelligence, JSAI-isAI 2015: New Frontiers in Artificial Intelligence* (pp. 528–546). Springer.

Kudo, K., & Ohtsuki, T. (2008). Adaptive Variability in Skilled Human Movements. *Transactions of the Japanese Society for Artificial Intelligence*, *23*(3), 151–162. Retrieved from https://www.jstage.jst.go.jp/article/tjsai/23/3/23_3_151/_pdf

Lipsitz, L. A., & Goldberger, A. L. (1992). Loss of "Complexity" and Aging. *Jama*, *267*(13), 1806. https://doi.org/10.1001/jama.1992.03480130122036

Manor, B., Costa, M. D., Hu, K., Newton, E., Starobinets, O., Kang, H. G., … Lipsitz, L. A. (2010). Physiological complexity and system adaptability: evidence from postural control dynamics of older adults. *Journal of Applied Physiology*, *109*(6), 1786–1791. https://doi.org/10.1152/japplphysiol.00390.2010

Manor, B., & Lipsitz, L. A. (2013). Physiologic complexity and aging: Implications for physical function and rehabilitation. *Progress in Neuro-Psychopharmacology and Biological Psychiatry*, *45*(617), 287–293. https://doi.org/10.1016/j.pnpbp.2012.08.020

Marmelat, V., Torre, K., & Delignières, D. (2012). Relative roughness: An index for testing the suitability of the monofractal model. *Frontiers in Physiology*, *3 JUN*(June), 1–11. https://doi.org/10.3389/fphys.2012.00208

Nicolis, G., & Prigogine, I. (1977). *Self-organization in nonequilibrium systems: from dissipative structures to order through fluctuations*. Wiley. Retrieved from https://books.google.com/books?id=mZkQAQAAIAAJ&pgis=1

Nonaka, T. (2013). Motor Variability but Functional Specificity: The Case of a C4 Tetraplegic Mouth Calligrapher. *Ecological Psychology*, *25*(2), 131–154. https://doi.org/10.1080/10407413.2013.780492

Nonaka, T., & Bril, B. (2012). Nesting of asymmetric functions in skilled bimanual action: Dynamics of hammering behavior of bead craftsmen. *Human Movement Science*, *31*(1), 55–77. https://doi.org/10.1016/j.humov.2010.08.013

Nonaka, T., & Bril, B. (2014). Fractal dynamics in dexterous tool use: The case of hammering behavior of bead craftsmen. *Journal of Experimental Psychology: Human Perception and Performance*, *40*(1), 218–231. https://doi.org/10.1037/a0033277

Peng, C., Buldyrev, S. V., Havlin, S., Simons, M., Stanley, H. E., & Goldberger, A. L. (1994). Mosaic organization of DNA nucleotides. *Physical Review E*, *49*(2), 1685–1689. https://doi.org/10.1103/PhysRevE.49.1685

Peng, C., Havlin, S., Stanley, H. E., & Goldberger, A. L. (1995). Quantification of scaling exponents and crossover phenomena in nonstationary heartbeat time series. *Chaos*, *5*(1), 82–87. https://doi.org/10.1063/1.166141

Pincus, S. M. (1991). Approximate entropy as a measure of system complexity. *Mathematics*, *88*(March), 2297–2301. https://doi.org/10.1073/pnas.88.6.2297

Richman, J. S., R., M. J., & Moorman, J. R. (2000). Physiological time-series analysis using approximate entropy and sample entropy. *Am J Physiol Heart Circ Physiol*, *278*(6), H2039-2049. https://doi.org/10.1103/physreva.29.975

Roerdink, M., De Haart, M., Daffertshofer, A., Donker, S. F., Geurts, A. C. H., & Beek, P. J. (2006). Dynamical structure of center-of-pressure trajectories in patients recovering from stroke. *Experimental Brain Research*, *174*(2), 256–269. https://doi.org/10.1007/s00221-006-0441-7

Schmit, J. M., Riley, M. A., Dalvi, A., Sahay, A., Shear, P. K., Shockley, K. D., & Pun, R. Y. K. (2006). Deterministic center of pressure patterns characterize postural instability in Parkinson's disease. *Experimental Brain Research*, *168*(3), 357–367. https://doi.org/10.1007/s00221-005-0094-y

Shumway-Cook, A., & Woollacott, M. H. (2013). *Motor Control: Translating Research Into Clinical Practice*. Lippincott Williams & Wilkins. Retrieved from https://books.google.com/books?id=BJcL3enz3xMC&pgis=1

Sleimen-malkoun, R., Temprado, J., & Hong, S. L. (2014). Aging induced loss of complexity and dedifferentiation : consequences for coordination dynamics within and between brain , muscular and behavioral levels. *Frontiers in Aging Neuroscience*, *6*(June), 1–17. https://doi.org/10.3389/fnagi.2014.00140

Stergiou, N. (2016). *Nonlinear analysis for human movement variability*.

Suwa, M. (2013). Story-Telling and Encouragement as a Research Environment ―What is "Researchers Learn from One Another"?―. *Artificial Intelligence*, *28*(5), 695–701.

Turvey, M. T. (1990). Coordination. *American Psychologist*, *45*(8), 938–953.

Van Orden, G. C., Holden, J. G., & Turvey, M. T. (2003). Self-organization of cognitive performance. *Journal of Experimental Psychology. General*, *132*(3), 331–350. https://doi.org/10.1037/0096-3445.132.3.331