Task demand changes motor control strategies in vertical jumping

Emily J. Cushion[1]*, John Warmenhoven[2], Jamie S. North[1], and Daniel J. Cleather[1,3]

[1] Faculty of Sport, Health and Applied Science, St Mary's University, Twickenham, United Kingdom

[2] Exercise and Sports Science, Faculty of Health Sciences, The University of Sydney, Lidcombe, Australia

[3] Institute for Globally Distributed Open Research and Education (IGDORE)

***Correspondence:**
Emily J. Cushion
St Mary's University
Waldegrave Road.
Strawberry Hill
Twickenham
TW1 4SX
emily.cushion@stmarys.ac.uk

Abstract

The purpose of this study was to examine the motor control strategies employed to control the degrees of freedom when performing a lower limb task with constraints applied at the hip, knee and ankle. Thirty-five individuals performed vertical jumping tasks: hip flexed, no knee bend and plantar flexed. Joint moment data from the hip, knee and ankle were analysed using principal component analysis (PCA). In all PCA performed, a minimum of two and maximum of six principal components (PC) were required to describe the movements. Similar reductions in dimensionality were observed in the hip flexed and no knee bend conditions (3PCs), compared to the plantar flexed condition (5PCs). A proximal to distal reduction in variability was observed for the hip flexed and no knee bend conditions but not for the plantar flexed condition. Collectively, the results suggest a reduction in the dimensionality of the movement occurs despite the constraints imposed within each condition and would suggest that dimensionality reduction and motor control strategies are a function of the task demands.

Keywords: principal component analysis, vertical jumping, degrees of freedom, constraints, proximal to distal pattern

Introduction

A question which has long concerned scientists and researchers with an interest in human movement, is how individuals are able to control the many degrees of freedom (DOF) whilst performing smooth, flowing, and seemingly effortless actions. This has been termed the DOF problem by Bernstein (1967). When performing motor tasks, there will be more than one coordination pattern available to the individual, which is said to represent redundancy of the motor system (Newell & Vaillancourt, 2001). This motor redundancy, however, provides functional benefit to the performer as it allows flexibility and adaptability to the ever-changing performance constraints (Latash, Scholz, & Schöner, 2007; Santello, Baud-bovy, & Jörntell, 2013). Whilst many solutions exist to satisfy a task or achieve a particular outcome, it is often the case that a select few strategies will be adopted. It is proposed that the system produces synergies (covariance between joints) to reduce the complexity of controlling many DOFs (Latash et al., 2007). Evidence for such synergies has been presented using statistical approaches such as principal component analysis (PCA) which reduce the dimensionality of data. Using this approach, Shemmell et al. (2007) found just two principal components (PCs) were required to describe the relationship between three joint angles during the swing phase of a walking task, suggesting a coupling or synergy between these joints. Similar findings have also been observed in tasks such as walking (Deluzio & Astephen, 2007; Nazifi, Yoon, Beschorner, & Hur, 2017), running (Phinyomark, Hettinga, Osis, & Ferber, 2015), juggling (Zago et al., 2017) and cello bowing (Verrel, Pologe, Manselle, Lindenberger, & Woollacott, 2013).

The existence of synergies has also been demonstrated across task variations; for example, grasping tasks to different objects (Santello, Flanders, & Soechting, 1998), performing the same task with and without an added constraint (Dounskaia & Wang, 2014), or performing a task at different speeds (Shemmell et al., 2007) or loads (Soechting & Lacquaniti, 1981). When performing a free stroke drawing task under either a constrained (movement restricted to the horizontal plane) or unconstrained condition (no movement restrictions in place), participants demonstrated preferred coordination patterns which were similar for both conditions (Dounskaia & Wang, 2014). This has also been observed when comparing thirty upper limb activities of daily living, where a limited number of time-series waveforms could be used to describe all movement tasks (Averta, Santina, Battalia, Felici, Bianchi, & Bicchi, 2017). Collectively, these studies provide a body of evidence which demonstrates that even with modifications to a task, common motor patterns emerge to carry out the movement, consistent with the proposition that the complexity of movement is reduced through couplings within the system. Examination of how the system reduces the complexity of the task and importantly the degree of reduction in dimensionality across tasks can provide useful information about how motor patterns adapt to different constraints under which they are performed.

Many movement tasks require the control of proximal and distal segments for efficient movement outcomes. However, noise disturbances applied to proximal or distal joints can differentially affect the overall movement dynamics and control of the task, suggesting the system is able to adapt to different contexts (Huffenus, Amarantini, & Forestier, 2006; Nguyen & Dingwell, 2012; Salmond, Davidson & Charles, 2017). An approach to gain insights into the motor control strategies employed to control the degrees of freedom present within a task is to apply constraints to parts of the system (e.g., see Eriksen, Lorås, Pedersen, & Sigmundsson, 2018; Nguyen & Dingwell, 2012). For instance, it has been shown that the proximal to distal motor control strategies of the upper limb are affected when joint motion is restricted in drummers and non-drummers. Specifically, both groups were affected when a proximal constraint was applied, but drummers were more efficient when a distal constraint was applied (Eriksen et al., 2018). In an upper limb model, noise added to the distal joint resulted in greater endpoint error than when noise was added to the proximal joint, suggesting a reduction in variability at the distal joint is advantageous for reducing endpoint errors (Nguyen & Dingwell, 2012). Equally, the addition of constraints at proximal and distal joints may be compensated for by the system, such that motor performance is not impaired (Huffenus et al., 2006). Within a motor learning context, control of proximal to distal joints has been shown to differ, with some suggestions of more control over proximal joints before distal joints when learning new tasks (Furuya & Kinoshita, 2007; Yang & Scholz, 2005; Verrel et al., 2013), whereas others have shown a reduction in motion of distal joints when holding objects (Konczak, Velden, & Jaeger, 2009).

To date, much of the published literature has examined proximal and distal control strategies in upper limb tasks (e.g., see Eriksen et al., 2018; Furuya & Kinoshita, 2007; Huffenus, Amarantini, & Forestier, 2006; Serrien & Baeyens, 2017; Verrel et al., 2013). However, the nature of upper limb tasks usually requires the distal aspect of the limb (e.g. hand) to be free, whereas for most lower limb tasks the distal aspect (e.g. foot) is usually in contact with a surface, either throughout (e.g. sit to stand) or in portions of the movement task (e.g. walking, jumping and running). Consequently, this may impact the proximal and distal motor control strategies and control of DOF throughout the movement and warrants further investigation.

In order to establish the control of the DOF within a task, various methods of statistical analysis have been employed such as cross correlation, vector coding and continuous relative phase analysis (Newell, Broderick, Deutsch, & Slifkin, 2003; Hong & Newell, 2006a). However, these methods do not effectively allow the analysis of multiple DOF and so, within the current study, a PCA was used. With this approach, the reduction in the dimension of the dataset is a representation of the functional DOF within a specific task (Daffertshofer, Lamoth, Meijer & Beek, 2004; Li., 2006; Nordin & Dufek, 2016). PCA applied in this way has been used to assess the control of DOF in several tasks including simulated skiing (Hong & Newell, 2006b), soccer chipping (Hodges, Hayes, Horn & Williams, 2005) and cello bowing (Verrel et al., 2013). In addition to the application of PCA, this study focused on the description of motor control through analysis of kinetic variables rather than kinematic variables which are more readily explored when examining the DOF of a movement (Furuya, Nakamura, & Nagata, 2014; Hong, & Newell, 2006). In particular, the joint moments of the lower limb were subjected to PCA within this study; allowing an analysis of how movement is produced and comparisons to be made with previous work using similar tasks (see Cushion, Warmenhoven. North & Cleather, 2019).

Therefore, the purpose of this study was to understand how the DOF of a lower limb task with constraints applied at the hip, knee and ankle are controlled. A vertical jump was chosen as a suitable task to study this, due to the requirement of a proximal to distal extension of the lower limb. The study focused on determining the changes in contribution of DOF between conditions, along with understanding the control of proximal to distal joints within the sagittal plane. To determine motor control strategies and the control of DOF, a multivariate statistical tool, principal component analysis (PCA) was used. This statistical method has been used previously to answer similar questions (see Cushion et al., 2019; Furuya et al., 2014; Hong & Newell, 2006a; Verrel et al., 2013). Based on previous research findings, such as that which have shown comparable joint torque patterns during the swing phase of gait at different speeds (Shemmell et al., 2007) and similarities in the joint torque time series across jumps performed with and without an arm swing (Cushion et al., 2019), it was hypothesised that despite the different constraints between each jump condition, the motor patterns observed would be very similar between conditions. Second, we hypothesised that the jump condition with an added constraint at the ankle, would show less reduction in the DOF due to this particular jumping task being more complex and placing greater motor control demands on the performer than the other jump conditions. Finally, we hypothesised a greater reduction in variability would occur at the distal joint (ankle) compared to the proximal joint (hip) regardless of jump condition due to the requirement for the distal segment (foot) to be in contact with the ground for the duration of the task (see Konczak et al., 2009).

Methods

Participants

Thirty-five healthy individuals (males = 22, females = 13) volunteered to take part in this study (mean ± SD; age = 26.0 ± 5.5 years, height = 174.8 ± 8.9 cm, body mass 78.5 ± 14.1 kg). They were free from musculoskeletal injuries and were provided with details of the study before written informed consent was obtained. The experimental procedure was approved by the ethics sub-committee at the institution where the research took place.

Procedure

Participants were required to attend one data collection session. This involved the collection of anthropometric measures (height and weight), before each participant was provided with a standardised shoe according to their shoe size. Eighteen reflective markers were placed on the pelvis and on the right lower limb. Data from the right limb was used for further analysis in accordance with previous work from Cleather et al. (2013). Markers were placed on the right and left anterior superior iliac spine and posterior superior iliac spine, lateral and medial femoral epicondyle, apex of lateral and medial malleolus, posterior aspect of calcaneus, tuberosity of fifth metatarsal and head of second metatarsal (Cleather & Bull, 2015). Three additional markers placed on rigid plates were attached to the mid-thigh and anterior tibial shaft, with an additional marker attached to the top of the foot. Kinematic data were collected using a Vicon motion capture system (Vicon MX System, Nexus 2.2 software, Vicon Motion Systems Ltd, Oxford, UK) with fourteen LED cameras tracking the reflective markers at a sampling frequency of 200Hz. Kinetic data were collected via two force plates positioned flush to the laboratory floor (Kistler Type 9287BA, Bioware 3.24 software, Kistler Instruments Ltd, Hampshire, UK), at a rate of 1000Hz and synchronised with the Vicon system.

Participants completed a standardised warm-up (bodyweight squats, lunges, inchworms, hip rotations and vertical jumps) prior to completing any vertical jumps. The three vertical jump conditions were: i) starting from a hip flexed position, ii) jumping without bending the knee and iii) jumping starting in a plantar flexed position. The current data collection was part of a larger collection of data where multiple types of jumps were performed across different testing sessions in a randomised order. As a result of this, not all participants completed each jump condition. Twenty-one participants completed the hip flexed and no knee bend conditions, and twenty-two participants completed the plantar flexed condition.

Prior to completing any jumps, participants were provided with instructions for the specific condition they were about to complete. The order in which participants completed the conditions was randomised to minimise order effects. For the hip flexed condition, participants were instructed to start the jump in a hip flexed position (legs straight with torso parallel to the ground) with hands on hips. Participants were then instructed to jump as high as possible from this position and maintain hands on hips throughout the jump. The no knee bend condition required participants to jump whilst trying to not bend at the knee. This jumping condition has been used in previous research (see de Graaf, Bobbert, Tetteroo & van Ingen Schenau, 1987). A cue of "jump maximally while maintaining straight legs" was provided in order to encourage this jumping strategy. Within the plantar flexed condition, participants were asked to start the jump in a maximal plantar flexed position, but which allowed them to maintain balance. An instruction to not touch the floor with their heels throughout the jump was also given and participants were instructed they could use an arm swing. Participants were instructed to perform all jumps maximally. A sequence of images are provided for each jump condition in Figure 1.

Figure 1 here

Participants completed five maximal effort trials for each jump condition with a self-selected recovery period between each trial to reduce any effects of fatigue. Participants were given a two-minute recovery period between the tasks if they completed more than one jump condition.

Data analysis

All data was filtered using a 5th order Woltring filter with a cut off frequency of 10Hz. The propulsive phase of the vertical jump was used for analysis and was defined as being from the point where the right anterior superior iliac spine marker moved below stationary height until take-off (which was defined as the point where the ground reaction force fell to zero). Net joint moments (NJM) in the sagittal plane were calculated for hip, knee and ankle using a standard inverse dynamics calculation (Winter, 2005) within the FreeBody software (Cleather & Bull, 2015). Sagittal plane NJM were used for further analysis for each jump condition. As trial length varied between participants, data was spline interpolated and time normalised from 0 to 101 data points.

2.4 *Statistical Analysis*

Within this study, hip, knee and ankle net joint moments were used within PCA. Using this approach has the advantage of retaining the spatiotemporal pattern in the time series data whilst detecting coordination patterns between each jump condition. The fundamental purpose of a PCA is to find a linear transformation that maps the raw data described in its original coordinate frame to a new coordinate frame with orthonormal bases. In the context of data analysis, the coordinate frame for the raw data is defined by the measured variables, but these variables may have some degree of correlation with one another. The new coordinate frame that is given by the PCA is defined by a set of new uncorrelated variables called the principal components (PC). For instance, for a dataset consisting of p variables observed at n different time-points, the raw data can be described by the $n \times p$ matrix X where the columns of X are the individual variables and the rows represent each observation (time-point). The transformation U then maps the raw data to the new coordinate frame defined by the PCs, such that the raw data in the new coordinate frame Z, is given by $Z = UX$.

PCA output produces a matrix with each column representing the coefficients of a PC, these are ordered based on the amount of variance explained. In this study, the PC score waveforms represented the time series of values for each PC, determined by multiplying the raw data matrix by the coefficients matrix. The score waveforms therefore show the temporal evolution of the PCs and can highlight differences, and similarities, in the dynamics of the movements.

Prior to running the PCA, all data was normalised to the peak hip joint moment of each trial (Joliffe & Cadima, 2016). Seven PCA were performed to analyse differences between conditions and these are outlined in Table 1. PCA were performed in Matlab (The MathWorks, Inc., M A, version 2017a) using the *pca* function.

Table 1 here

A linear mixed model was used to compare PC coefficient values between the three jumping conditions, hip flexed, no knee bend and plantar flexed. Participants were included as random factors as not all the same participants completed each jump condition. Bonferroni post hoc tests were performed to examine any statistically significant main effects. Statistical analysis was conducted in SPSS (IBM SPSS Statistics 24). The alpha level was set at $p < 0.05$.

Results

Analysis from PCAa showed four PCs were required to retain over 90% of the information within the dataset (Table 2). When combining all data for each jump condition separately (PCAc), three PCs were required to explain over 90% of the variance within the data set for the hip-flexed and no knee bend conditions, whereas five PCs were required for the plantar-flexed condition (Table 2).

Table 2 here

Figure 2 presents PC1, 2 and 3 waveforms for each jump condition and the loading factors for each joint in each jump condition from PC1, 2 and 3. Data within this figure is from PCAc.

Figure 2 here

A multilevel model was conducted to compare PC1, 2 and 3 loadings from data obtained in PCAj. Analysis of PC1 loadings showed there was a significant interaction between jumps and joints ($F (4, 153.807) = 7.891$, $p = 0.000$). PC1 loading for the hip during the plantar flexed jump was significantly higher than the hip flexed condition. Likewise, PC1 loading was significantly higher in the no knee bend condition compared to the hip flexed condition and plantar flexed condition for the ankle (Figure 3, A). No significant differences were observed for PC2 loadings (Figure 3, B). Analysis from PC3 loading values showed there was a significant interaction between jumps and joints ($F (4, 158.399) = 2.928$, $p = 0.023$), with a greater loading observed at the knee in the plantar flexed condition, compared to the no knee bend condition and a significantly smaller loading in the no knee bend condition compared to the hip flexed condition (Figure 3, C).

Figure 3 and Table 3 show results from PCAj. For each PCA of this type only three PCs were retained.

Figure 3 here

Table 3 here

Average net joint moments for each jump condition across joints are presented in Figure 4. The data has been flipped for easier visualisation of the waveforms.

Figure 4 here

Discussion

The aim of the current study was to understand motor control strategies employed in vertical jumps under different task constraints and to determine the control of the functional DOF within each task. Specifically, participants completed vertical jumps with a constraint applied to either the hip, knee or ankle joint. Consistent with our first hypothesis, we found similarities in motor patterns between all conditions as assessed through comparing PC score waveforms. We also hypothesised that a reduction in the dimension of the DOF would occur for each condition, but this would be specific to the demands of the given task. The results were consistent with this hypothesis, as evidenced by only four PCs required to describe the hip, knee and ankle joint moment data within the hip flexed and no knee bend conditions, in comparison to six PCs required with the plantar flexed condition, demonstrating the increased complexity of the system. The data also showed slight differences in variation at the proximal and distal joints, with a proximal to distal decrease in variability occurring for hip flexed and no knee bend conditions. The plantar flexed condition was again different with the least variation occurring at the knee joint.

The results reported here show that the dimensionality of jumping with added constraints can be reduced to only a few functional DOF. Within each PCA performed (PCAa, PCAc, PCAj, PCAcj) a maximum of six PCs and a minimum of three PCs were retained. This reduction in dimensionality of complex coordinated movements has been shown in other tasks such as walking (Mah, Huliger, Lee & O'Callaghan, 1994), catching (Bockemühl, Troje & Durr, 2010), pointing (Lee, Corcos, Shemmell, Leurgans, & Hasan, 2008) and jumping (Cushion et al., 2019). In previous work using a jumping task, a maximum of three PCs were required to describe all joint moment waveforms when jumping under constrained (no arm swing) and unconstrained (use of arm swing) conditions (Cushion et al., 2019). Despite the different constraints applied in the current study and those employed by Cushion et al. (2019) it can be argued there is similarity in the underlying movement patterns required to perform jumping tasks, based on the similarity in the temporal shape of the PC score waveforms for each jump condition. This should be considered with some caution, however, as quantifying the mechanics of movement from statistical data can be challenging (Cushion et al., 2019; O'Connor & Bottum, 2009).

In contrast to previous studies comparing movements with added constraints (Lee, Roan & Smith, 2009), the dimensionality reduction in the current study was not the same for each condition. The hip, knee and ankle joint moment waveforms could be captured with three PCs for the hip flexed and no knee bend conditions, albeit with slight differences in the variance accounted for by each PC. In contrast, the requirement to jump starting in a plantar flexed position increased the number of PCs required to describe the dataset to five PCs. It is possible that the different movement requirement of this task, with the use of an arm swing and the additional balance requirement, increased the need for the additional PCs. It has previously been demonstrated that increasing task demand/difficulty increases the amount of PCs required, possibly due to the need to explore more movement options (Federolf, Roos & Nigg, 2013; Nordin & Dufek, 2016).

Despite some differences in the reduction in dimensionality between tasks, qualitatively, there is similarity in the pattern of waveforms within each condition. This can be observed in Figures 2 and 3 where comparisons of the temporal shape of PC waveforms are made across each jump condition and between each joint. Whilst the shape of the waveforms are similar, the information within each PC varies as evidenced when examining PC loadings. PC loadings provide detail of how much specific variables are weighted on each PC. For instance, based on the results from PCAj, a significant difference in loadings was observed in PC1 at the hip between the plantar flexed condition and hip flexed condition, as well as at the ankle between the plantar flexed and no knee bend condition and hip flexed and no knee bend condition. Furthermore, this is evidenced when considering the loadings between each condition from PCAc. For the plantar flexed condition, the hip and knee moments are almost entirely described by PC1, there is very little contribution of the PC2 or PC3 to the hip and knee moments. In contrast, the ankle within this condition is described by a combination of PC1, PC2 and PC3. This would indicate a coupling between the hip and knee, such that they move in phase with each other, as is also demonstrated with peak hip and knee joint moments occurring at similar time points (Figure 4). This coupling and loading pattern were not as clearly observed for the other two conditions. Specifically, within the hip flexed condition, we can observe similarity in waveforms for the hip and knee moments, but as observed in Figure 4, the peaks show a proximal to distal pattern. Here, it is the combination of PC2 that shifts the peak of PC1 to give the hip moment. Whereas, in the no knee bend condition, again we observe similar peaks for the hip and knee joint moment, however the wavelength for the hip is much larger. Here it is the combination of PC3 and PC1 that is important. The relative weight of PC3 on the hip increases the wavelength of PC1 to produce the hip moment. This difference in the relative weighting of each variable to each PC, changes the timing or the wavelength for each joint moment. These observed differences in the motor strategies for each condition would lend support to the concept of motor equivalence, where the same movement outcome can be achieved under varying conditions (jump conditions in this study) and limb control strategies (joint moment production in this study). The outcome of the current tasks was to raise the centre of mass as high off the ground as possible, but this was achieved uniquely for each condition. The concept of motor equivalence is similarly supported within the literature (see Mattos, Kuhl, Scholz & Latash, 2013; Verrel et al., 2013).

It is also important to consider the variation (differences in the number of PCs required to describe over 90% of the dataset) for each PCA performed. Within PCAa there are many sources of variation, including individuals, trials, joint moments and jump conditions, but this dataset could be reduced to only four PCs. In contrast, the impact of variance coming from jump conditions was removed in PCAc, resulting in a reduction in PCs required for the hip flexed and no knee bend conditions, but an increase in PCs for the plantar flexed condition. It is therefore likely that the fourth PC required in PCAa captures the variation within the plantar flexed condition. When performing PCAa without the plantar flexed condition only three PCs were retained, supporting our proposal that increased variation from the plantar flexed condition causes an increase in the amount of PCs required to capture the information within the dataset. In PCAj, sources of variation came from individuals, trials and jumps, removing variance from joint moments, which resulted in only three PCs being retained for each condition. When joint moment variance was removed in PCAj the number of PCs describing all conditions reduced to three, and so it is therefore likely the PCs within the current study partly describe variance in the joint moments between each jump condition. In the previous research by Cushion et al. (2019), it was also postulated the PCs described variation in the joint moments. Furthermore, it is likely the PCs also describe the individual variation, given there was no reduction in PCs below three when joint moment variance was removed in PCAj. This can also be shown within PCAcj analysis. Here, variance is derived from individuals and trials. Given six PCs were required for the hip joint within the plantar flexed condition, it would suggest there is variation within individuals performing this task.

The control of proximal and distal segments may be impacted by constraints on the system such that changes in movement strategies occur in order to satisfy the task goal (Salmond et al., 2017; Nguyen & Dingwell, 2012; Huffenus, et al., 2006). In the current study a proximal to distal reduction in variability was observed for the hip flexed and no knee bend conditions, however this trend was not observed in the plantar flexed condition. Regardless of the jump condition, the greatest variability occurred at the hip, but there were condition specific differences in the proportion of variance explained by the first principal component. This suggests that applying a constraint proximally or distally differentially affects the motor control strategy adopted. The plantar flexed condition did not follow the same proximal to distal reduction in variability and it may be that the additional requirement for balance within this task meant participants had to explore movement options at the distal joint in order to satisfy the requirement to maintain balance (Federolf, et al., 2013). It is likely the specific task requirements contribute to the control of proximal and distal joints rather than there being one inherent control strategy (Vaillancourt & Newell, 2002).

In the present study the focus of analysis was on the first three PCs, however there is evidence to suggest intermediate and higher order PCs reveal further differences between conditions or individuals, which would not have been apparent with only an analysis of lower order PCs (Daffertshofer, et al., 2004; Lamoth, Daffertshofer, Meijer, & Beek, 2006; Maurer, von Tscharner, Samsom, Baltich, & Nigg, 2013; Phinyomark et al., 2015). Therefore, future analyses should seek to determine if higher order PCs when jumping with constraints can reveal further detail into the control process of these tasks. Equally, the analyses performed in the current study were focused on assessing movement within one session. There is evidence to suggest that the dimensionality of movement changes with subsequent practice of a task (Majed, Heugas, & Siegler, 2017; Newell & Vaillancourt, 2001). Given that the results reported in this study showed the plantar flexed condition required the greatest number of PCs, it would be interesting for researchers to investigate how this might change over the course of practice and if the dimensionality of this movement may be further reduced.

Conclusion

This study has highlighted the system's ability to adapt to constraints in a multi-joint task. Despite constraints being applied at each lower limb joint, there were both similarities and differences in the motor control strategies employed to realise the task goal. The dimensionality of each movement was similarly reduced for hip flexed and no knee bend conditions, with a lesser reduction occurring for the plantar flexed condition, suggesting greater complexity within the system when this constraint was added. Equally, the temporal pattern of movement production share resemblances across each condition. In contrast, differences were observed in loadings between conditions, suggesting the utilisation of each joint differed in each condition to ensure the task was performed. Interestingly it was the constraint applied at the ankle which stood out as showing the greatest difference in strategy, with the largest variation in the movement and lack of a clear proximal to distal reduction in variability. With the added balance requirement of this task, it is likely the task demands constrain how the system controls the many DOF. Collectively the findings reported in this study support the notion that the CNS utilises redundancy within the motor system to carry out specific tasks under differing constraints.

Word Count: 4827

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Table 1. Description of data used within each PCA.

PCA Descriptor	Time Series Data Used	Number of separate analyses	Input Matrices
PCAa	all participants, trials and joints from all jump conditions	1	101 x 947
PCAc	all participants, trials and joints from each jump condition separately	3	HF: 101 x 300 NKB: 101 x 314 PF: 101 x 333
PCAj	all participants and trials from all jump conditions conducted separately for each joint	3	Hip: 101 x 317 Knee: 101 x 317 Ankle: 101 x 317
PCAcj	All participants and trials from each jump condition conducted separately for each joint and each condition	9	HF – Hip, knee and ankle: 101 x 100 NKB – Hip, knee and ankle: 101 x 106 PF - Hip, knee and ankle: 101 x 111

Table 2. Percentage of explained variance from PCAa and PCAc.

	PC1	PC2	PC3	PC4	PC5	Total
PCAc						
HF	70.5	14.7	5.7			90.9
NKB	63.2	21.2	7.9			92.3
PF	62.9	13.8	6.2	4.4	3.2	90.5
PCAa (All Conditions)	63.4	17.3	7.2	4.2		93.1
PCAa (sub analysis)						
HF&NKB	65.7	18.6	7.2			91.5
HF&PF	64.8	14.9	5.6	4.9		90.1
NKB&PF	61.3	18.1	7.7	4.2		91.3

HF = hip flexed, NKB = no knee bend, PF = plantar-flexed

Table 3. Percentage of explained variance from PCAj.

	PC1	PC2	PC3	PC4	PC5	PC6	Total
PCAj							
Hip	69.7	19.5	4.6				93.8
Knee	67.5	18.0	7.7				93.2
Ankle	74.1	15.7	4.1				93.9
PCAcj							
HF							
Hip	69.7	15.3	5.1				90.1
Knee	74.8	12.8	7.1				94.7
Ankle	83.7	8.9					92.6
NKB							
Hip	47.9	26.5	11.9	4.9			91.2
Knee	70.5	22.3					92.8
Ankle	77.7	16.4					94.1
PF							
Hip	59.9	13	6.6	4.8	3.9	2.9	91.1
Knee	70.4	15.7	5.5				91.6
Ankle	64.8	17.6	6.3	3.1			91.8

HF = Hip flexed, NKB = no knee bend, PF = plantar flexed

Figure Legends

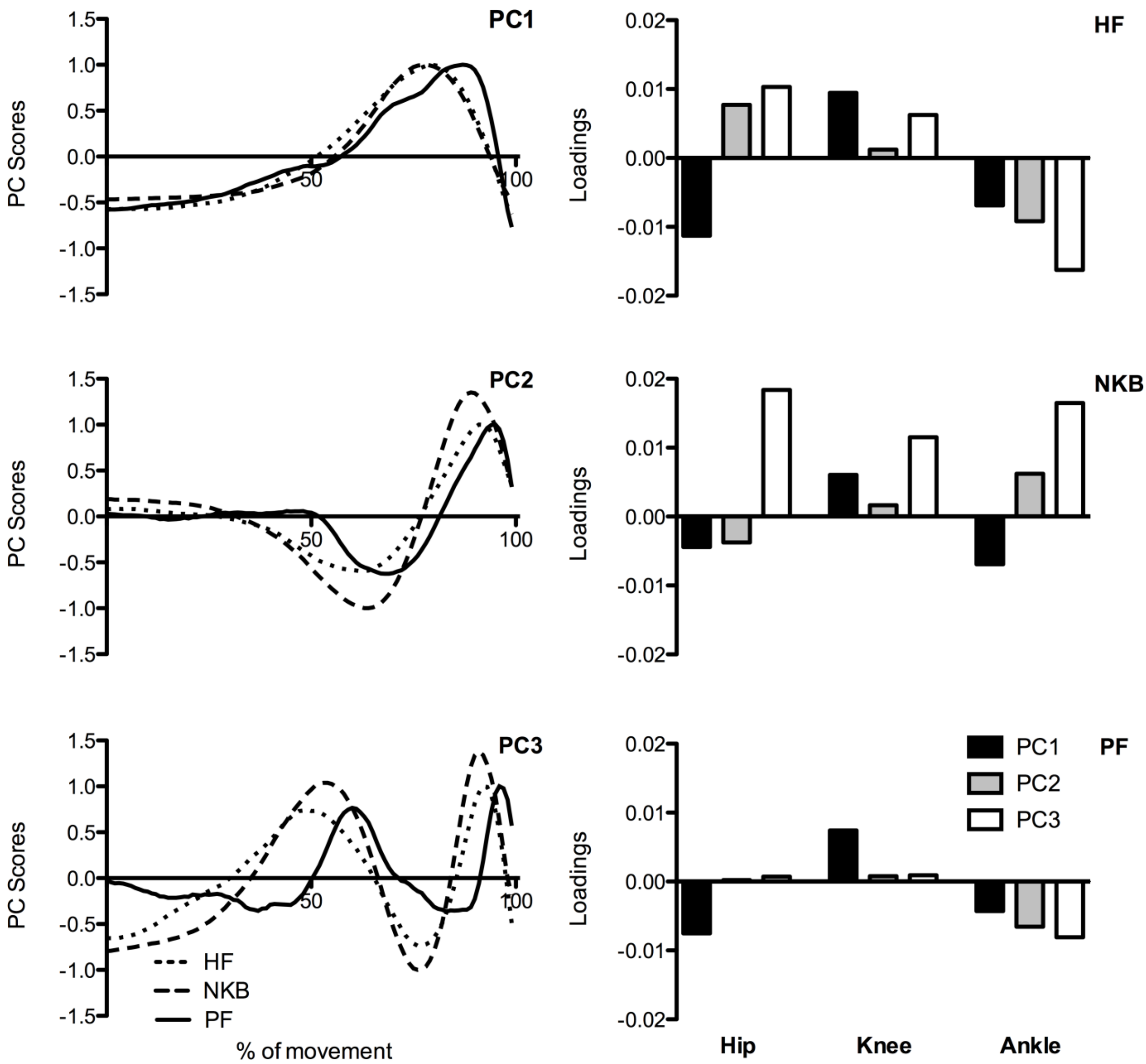
Figure 1. Starting position and movement sequence for each jump condition a) hip flexed b) no knee bend and c) plantar flexed.

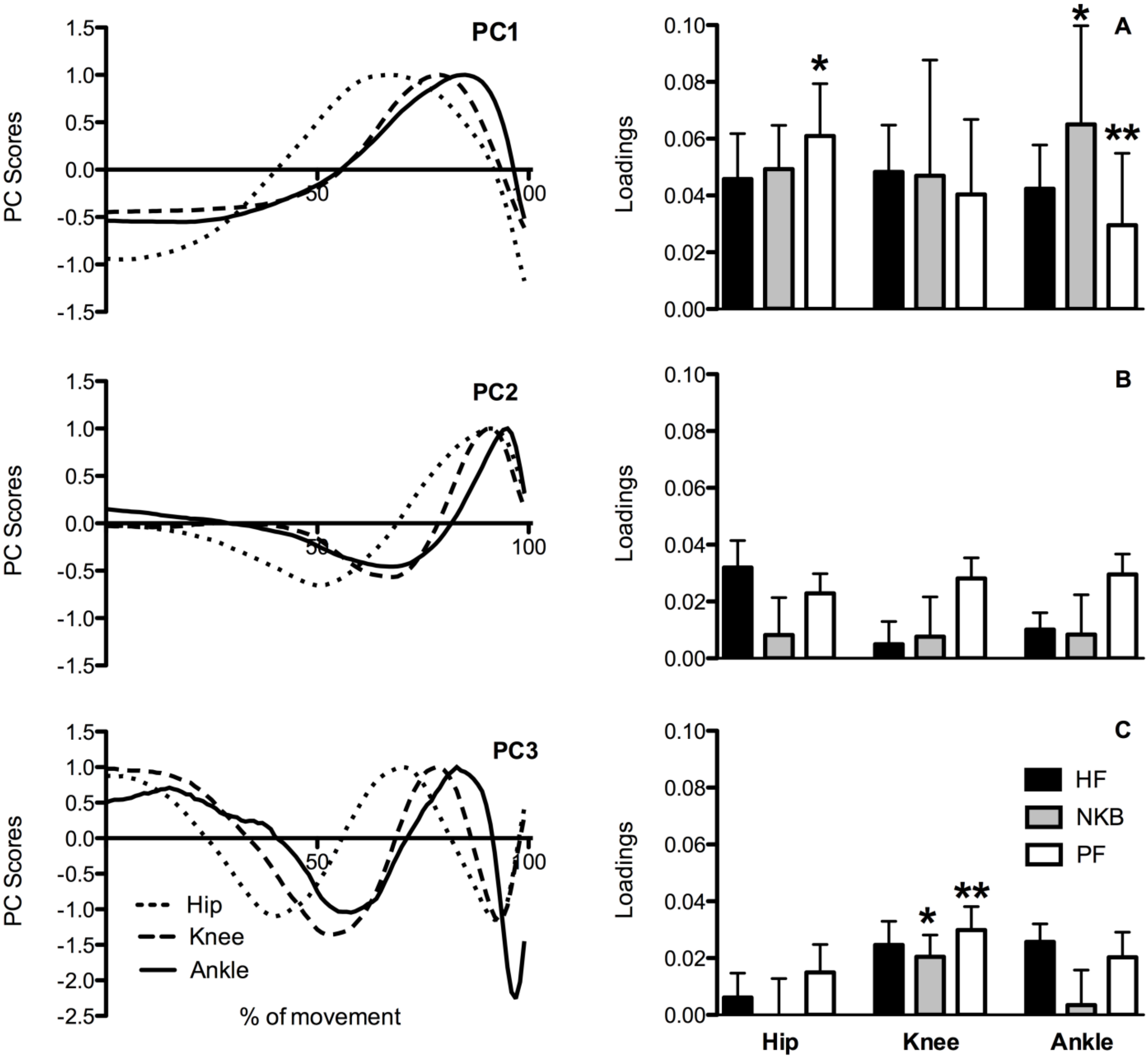
Figure 2. PC1, 2 and 3 score waveforms for each jump condition (left panel) from PCAc and averaged loadings on PC1, 2 and 3 for each jump condition (right panel). HF = hip flexed, NKB = no knee bend, PF = plantar-flexed.

Figure 3. PC1, 2 and 3 waveforms from PCAj (left panel). PC1 (A), PC2 (B) and PC3 (C) loadings from PCAj for each jump condition (means ± SD) (right panel). HF = hip flexed, NKB = no knee bend, PF = plantar flexed *Indicates significant difference from HF condition. **Indicates significant difference from NKB condition.

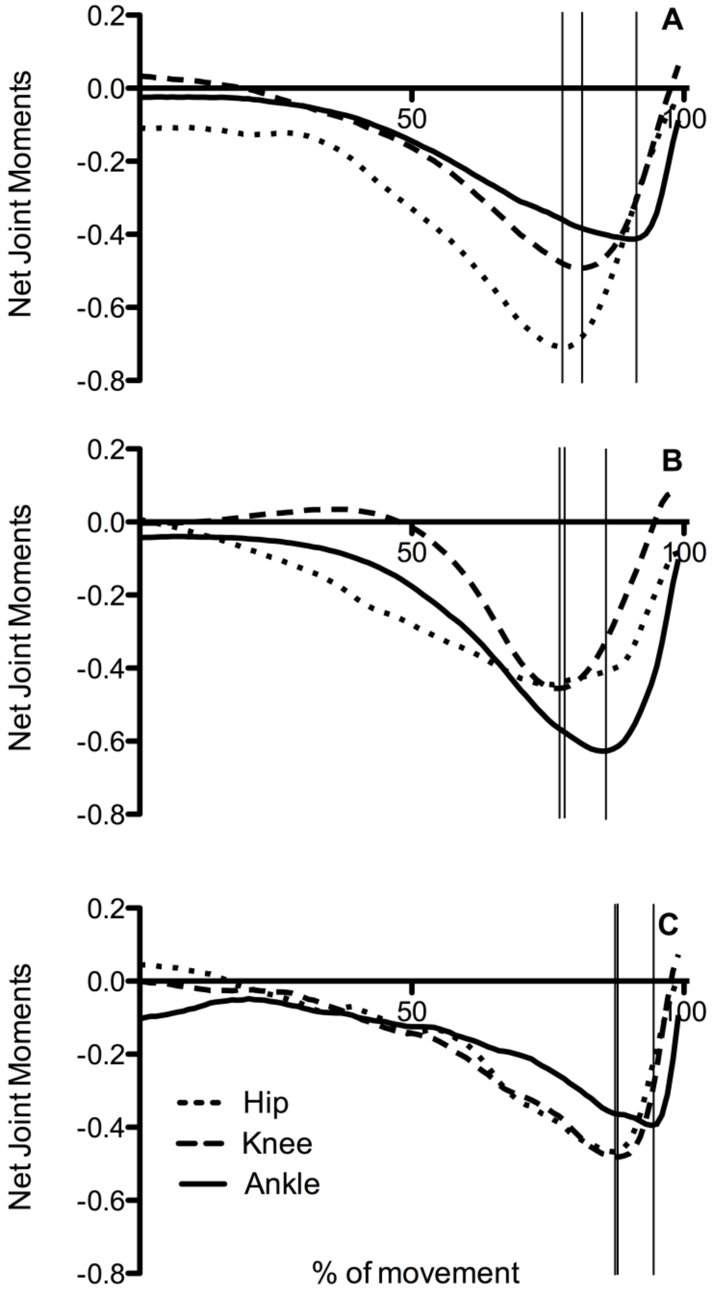
Figure 4. Net joint internal moments for each joint across each jump condition. A = hip flexed, B = no knee bend, C = plantar flexed. Negative moments indicate extension. Knee joint moment data has been flipped to improve visual comparison between peaks. Vertical lines indicate where peak joint moment occurred.


A
B
C


PC1
PC2
PC3
PC Scores
% of movement
50
100
1.5
1.0
0.5
0.0
-0.5
-1.0
-1.5
HF
NKB
PF
Loadings
0.02
0.01
0.00
-0.01
-0.02
PC1
PC2
PC3
Hip
Knee
Ankle



PC1
PC2
PC3
PC Scores
% of movement
Hip
Knee
Ankle
Loadings
A
B
C
HF
NKB
PF
*
**


A
B
C
0.2
0.0
-0.2
-0.4
-0.6
-0.8
50
100
Net Joint Moments
Hip
Knee
Ankle
% of movement

702