Analysing patterns of coordination and patterns of control using novel data visualisation techniques in vector coding

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Analysing patterns of coordination and patterns of control using novel data visualisation techniques in vector coding.

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Highlights

- • Combining colour maps with profiling techniques provide effective data visualisation
- • Coupling angle mapping of time series data details segmental coordination
- • Segmental dominancy profile offers intuitive summary on coupling angle distribution
- Inter-data point range of motion profiling helps to understand segmental dominance
- • Inter-data point range of motion profiles patterns of movement control

Abstract

Objective: Vector coding is a non-linear data analysis technique that quantifies inter-segmental coordination and coordination variability. The traditional approach of reporting time-series data from vector coding can be problematic when overlaying multiple trials on the same illustration. The objective of this study was to describe and present novel data visualisations for displaying the coordination pattern, segmental dominancy, range of motion on an angle-angle diagram, and coordination variability. This allows for a comparison of data across multiple participants with a focus on single subject analysis.

Methods: Novel data visualisation techniques that involve the use of colour and data bars to map and profile coordination pattern and coordination variability data. The introduction and profiling of inter-data point range of motion quantifies range of motion of the dominant segment on an angle-angle plot and illustrates patterns of movement control. As an example, the dataset used the Istituto Ortopedico Rizzoli foot model to describe rearfoot-forefoot and shank-foot coordination during stance.

Results: The use of colour mapping provides the option to inspect an entire dataset and to compare data across multiple participants, groups, and segment couplings. Combining coupling angle mapping with segmental dominancy profiling offers an intuitive and instant summary on coupling angle distribution. The novel inclusion of inter-data point range of motion profiling provides meaning to the interpretation of segmental dominancy data and demonstrates distinct patterns of movement control.

Conclusions: The use of colour mapping and profiling techniques highlighted differences in coordination pattern and coordination variability data across several participants that questions the interpretation and relevance of reporting group data. Colour mapping and profiling techniques are ideal reporting methods to compliment prospective multiple single-subject design studies and to classify commonalities and differences in patterns of coordination and patterns of control between individuals or trials. The data visualisation approaches in the current study may provide further insight on overuse injuries, exercise prescription and rehabilitation interventions.

Key Words:
Vector coding, coordination, variability, coupling angle mapping, segmental dominancy profiling

1. Introduction

Several biomechanical degrees of freedom are available for the provision of executing a goal-orientated movement task. From a dynamical systems perspective, the number of degrees of freedom is reduced over time that leads to the development of coordinative structures that enable a movement task to be performed in an effective manner [1]. These preferred coordination patterns are arranged from previous experiences and constraints imposed through the complex relationships between control parameters (i.e. the task, organism, and environment) [1–3]. In addition, it is the interaction between these constraints and perceptual behaviour that governs movement variability which is central to the self-organising process in the human movement system [4,5].

An angle-angle diagram is the plot of one angle as a function of another angle, which provides a qualitative illustration of the coordination patterns between body segments during movement (Fig. 1a). However, a detailed view on coordination is not possible from a qualitative perspective due to subtle changes in segment orientations. Recent developments in vector coding have provided a quantitative measure of the shape of the angle-angle diagram by using non-linear equations to calculate the vector orientation between adjacent data points [6]. The vector orientation can range between 0-360° and this circular variable is referred to as the coupling angle (Fig. 1b) [7]. Based on the circular position, the coupling angle can be assigned to a coordination pattern classification. For example, a coupling angle of 50° indicates in-phase coordination (i.e. both segments are rotating in the same direction) and distal segment dominancy (i.e. distal segment rotation at that instant is greater than the proximal segment) [8].

Typically, the mean coupling angle and mean coordination variability is reported using a traditional time-series format, providing coordination pattern classification information on the right vertical axis [9–11]. Coordination variability is a circular statistic equivalent to a standard deviation in linear statistics. In general, mean coordination variability extends across coordination pattern classifications that signifies the mean coupling angle and associated coordination pattern is not a representative classification across all individuals [8,11,12] (Fig 1c). The lack of generalisability emphasises the impact of a constraints led approach to the development of individual-specific coordinative structures, which raises the issue and value on the technique of pooling individual data and use of inferential statistics in this instance [4]. In addition, several studies have shown that group analysis techniques cannot detect modified movement strategies of individuals participants [13–16]. Indeed, pooling group data may mask individual variation that results in a 'non-significant effect' although a positive or negative response to an intervention may be substantial for certain individuals [17–20]. Instead, presenting empirical data through a single-subject research design approach can supplement a group design and be an alternative when the sample size is low [15,18,21], which tends to be the case in biomechanics research [22,23].

Several studies [24–27] have demonstrated the usefulness of multi-segment foot models to understand the complexity of foot and ankle kinematics. Whilst vector coding has furthered our understanding of the relationship between various segments within the foot [28–30], there is still a paucity of information on the generalisability of the findings. This is mainly due to methodological considerations, such as kinematic models and presenting group average data, resulting in a wide variability in kinematic data between subjects. In addition, although vector coding can characterise the shape of an angle-angle plot and detail the coordination between segments at each instant in time but is unable to provide a measure of control (i.e. range of motion). For example, during gait several individuals may display similar patterns of coordination between the shank and the foot, however the magnitude of range of motion needs to be considered to identify any relevant biomechanical dysfunction (i.e Ankle Equinus).

Interpreting coupling angle and coordination variability data using a traditional format can be difficult when attempting to decipher between time-series, particularly if multiple trials are overlapped on the same figure (Fig. 1 e/g). Furthermore, there is a clear need for effective data reporting approaches which involve the illustration of multiple trials within a single-subject design, and support a current data analysis technique such as 'coordination profiling' [31].

Therefore, this paper aims to describe novel data visualisation techniques for displaying coupling angle and coordination variability data that allows for a comparison of data across multiple participants, segment couplings and experimental conditions. This information is extremely important for understanding individual movement strategies and will provide effective management and monitoring of movement skill interventions. The dataset used in this study describes the shank-foot and forefoot-rearfoot coordination during the stance phase of walking gait.

2. Methods

The data collection procedures and experimental data were from our previous study from which ethical approval was sought and received from the University Research Ethics Committee [12]. In summary, data were obtained from ten male participants (mean ±standard deviation) age: 22.4 ±2.46 years, height: 180.3 ±7.18 cm, mass: 74.9 ±11.0 kg. An 8-camera motion capture system (Vicon, Oxford, UK.) was used to collect the trajectory of reflective markers that corresponds to the foot and ankle marker set proposed by Leardini et al. [26]. Marker coordinate data was processed in Visual3D (C-Motion, Inc., Germantown, MD, USA) using a low-pass Butterworth filter with a cut-off frequency of 6 Hz. Two AMTI-OR6 force platforms (Advanced Mechanical Technology, Inc., MA, USA) collected kinetic data at 1000 Hz that were used to identify initial contact and foot off. Participants were required to walk barefoot at a preferred walking speed. Five trials were recorded and data was normalized for time to 100% of stance.

2.1 Calculation of coupling angle and coupling angle variability:

For each instant (i) during the normalised gait cycle, the coupling angle (γ_i) was calculated based on the proximal segmental angles ($\theta_{P(i)}, \theta_{P(i+1)}$) and distal segmental angles ($\theta_D, \theta_{D(i+1)}$) according to equation (1):

$$\gamma_i = Atan\left(\frac{\theta_{D(i+1)}-\theta_{Di}}{\theta_{P(i+1)}-\theta_{Pi}}\right).\frac{180}{\pi} \qquad \theta_{P(i+1)} - \theta_{Pi} > 0 \tag{1}$$

$$\gamma_i = Atan\left(\frac{\theta_{D(i+1)}-\theta_{Di}}{\theta_{P(i+1)}-\theta_{Pi}}\right).\frac{180}{\pi} + 180 \qquad \theta_{P(i+1)} - \theta_{Pi} < 0 \tag{2}$$

The following conditions (3) were applied:

$$\gamma_i = \begin{cases} \gamma_i = 90 & \theta_{P(i+1)} - \theta_{Pi} = 0 \ \text{ and } \ \theta_{D(i+1)} - \theta_{Di} > 0 \\ \gamma_i = -90 & \theta_{P(i+1)} - \theta_{Pi} = 0 \ \text{ and } \ \theta_{D(i+1)} - \theta_{Di} < 0 \\ \gamma_i = -180 & \theta_{P(i+1)} - \theta_{Pi} < 0 \ \ and \ \ \theta_{D(i+1)} - \theta_{Di} = 0 \\ \gamma_i = Undefined & \theta_{P(i+1)} - \theta_{Pi} = 0 \ \text{ and } \ \theta_{D(i+1)} - \theta_{Di} = 0 \end{cases} \tag{3}$$

Coupling angle (γ_i) was corrected to present a value between 0º and 360º according to (4).

$$\gamma_i = \begin{cases} \gamma_i + 360 & \gamma_i < 0 \\ \gamma_i & \gamma_i \geq 0 \end{cases} \tag{4}$$

2.2 Averaging and variability calculation:

Due to directional nature of coupling angle, the average value for coupling angle (γ_i) across a number of trials (n) were calculated based on the average horizontal ($\bar{x}_i$) and vertical ($\bar{y}_i$) components at each instant using circular statistics [32].

$$\bar{x}_i = \frac{1}{n} \sum_{i=1}^{n} cos\, \gamma_i \tag{5}$$

$$\bar{y}_i = \frac{1}{n} \sum_{i=1}^{n} sin\, \gamma_i \tag{6}$$

The following (7) were applied to correct for the average coupling angle ($\overline{\gamma}_i$) to present a value between 0° and 360°.

$$\bar{\gamma}_i = \begin{cases} Atan\left(\frac{\bar{y}_i}{\bar{x}_i}\right).\frac{180}{\pi} & \bar{x}_i > 0, \bar{y}_i > 0 \\ Atan\left(\frac{\bar{y}_i}{\bar{x}_i}\right).\frac{180}{\pi} + 180 & \bar{x}_i < 0 \\ Atan\left(\frac{\bar{y}_i}{\bar{x}_i}\right).\frac{180}{\pi} + 360 & \bar{x}_i > 0,\ \bar{y}_i < 0 \\ 90 & \bar{x}_i = 0,\ \bar{y}_i > 0 \\ -90 & \bar{x}_i = 0,\ \bar{y}_i < 0 \\ undefined & \bar{x}_i = 0,\ \bar{y}_i = 0 \end{cases} \tag{7}$$

The length of average coupling angle $\bar{r}_i$ was calculated according to (8).

$$\bar{r}_i = \sqrt{\bar{x}_i^{\,2} + \bar{y}_i^{\,2}} \tag{8}$$

Coupling angle variability CAV_i was calculated according to (9).

$$CAV_i = \sqrt{2.(1 - \bar{r}_i)}.\frac{180}{\pi} \tag{9}$$

Subsequent coupling angle data were classified into one of four coordination patterns (Fig. 2) [8]. Angular rotation of two segments in the same direction refers to in-phase coordination whereas anti-phase coordination relates to two segments rotating in opposing directions. Since each quadrant of a unit circle represents 100 gradians, converting the coupling angle to a gradian provides a percentage outcome measure of proximal or distal segmental dominancy (9° is 10 gradian, 18° is 20 gradian, 27° is 30 gradian, etc.). Segmental dominance refers to a greater change in the angular range of either the proximal or distal segment at each instant in time during a movement cycle. For instance, a coupling angle of 45° is equal to 50 gradians and therefore 50%, indicating that angular rotation of the proximal and distal segment is contributing equally to a change in the relative angle [8].

The current study introduces the term "coupling angle mapping" which signifies a colour-scale approach to display changes in coordination pattern classifications across a movement cycle [16]. At each instant in time, the coupling angle is assigned to a colour based on the polar position within a coordination pattern classification. For simplicity, four colours were chosen, one for each quadrant of the unit circle. The transition between two scale shades of the same colour within the same phase coordination (i.e. in-phase or anti-phase) depicts a change from proximal to distal segment dominancy, or vice-versa. Data bars were used to profile segmental dominancy across a movement cycle (Fig. 3a). Vector coding informs only on changes in the phase coordination between two segments over time. Since range of motion is a universally accepted measure and description of human movement, "inter-data point range of motion" (IDP-ROM) of the dominant segment was quantified and superimposed over coupling angle mapping and segmental dominancy profiling (Fig. 3a).

Coordination variability mapping signifies the use of three colours to display the degree of variability between 0° (green) and 80° (red). The mean vector length (r - quantified between a value of 1 and 0) is a measure of the concentration regarding the circular direction of the coupling angle. As r decreases from 1 to 0 the dispersion of the coupling angle increases. Therefore, since coordination variability (circular equivalent of standard deviation) is quantified using an r value, an r value of 0 is equivalent to 81.07° [6]. Data bars represent the same coordination variability data but provide a distinct profile on coordination variability across a movement cycle (Fig. 3c).

For comparative purposes, stance was divided into three time normalised intervals to approximate the loading response (1-33%), midstance (34-66%) and propulsion (67-99%) [28,33].

3. Results

Group mean forefoot–rearfoot coordination in the frontal plane was generally in-phase with distal dominancy (forefoot) (Fig. 3a/6a), while sagittal plane foot-shank coordination was entirely in-phase with proximal dominancy (shank) (Fig. 3b/6b). Greater IDP-ROM was noted during early stance and late propulsion in both the sagittal and frontal plane, though IDP-ROM magnitude was greater for foot-shank coordination (Fig. 3a/b). Inconsistent IDP-ROM profiles were also seen across participants for frontal plane forefoot-rearfoot coordination (Fig. 3e) in comparison with similar IDP-ROM profiles for sagittal plane foot-shank coordination (Fig. 3f).

On frontal plane forefoot-rearfoot coordination, group mean coordination variability was high for an extended period during the latter stages of early stance and through midstance (Fig. 3c). This observation coincides with inter-participant differences in coordination patterns and frequent changes between in-phase and anti-phase coordination (Fig. 3e). Low group mean coordination variability for sagittal plane foot-shank coordination during loading response and late propulsion phase (Fig. 3d) corresponds with similar coordination patterns and segmental dominancy profiles across individual participants (Fig. 3f).

Coordination variability was generally higher across participants during midstance for frontal plane forefoot-rearfoot coordination. Though temporal variations in coordination variability profiles between participants during midstance would explain the high group coordination variability profile between 20-60% of stance (Fig. 4a). Coordination variability was considerably lower for sagittal plane foot-shank coordination across participants (Fig. 4b). Analysis of frontal plane forefoot-rearfoot coordination for one participant revealed high coordination variability during the transition between loading response and midstance which coincided with frequent transitions between phase coordination pattern classification (in-phase to anti-phase and vice versa) (Fig. 5).

4. Discussion

The suitability and impact of data visualisation should not be overlooked. It has been suggested that clinical judgement can be attained through inspecting graphic data that can detail the reliability, uniformity, and systematic measurement of intervention effects [20,21,34]. The purpose of this paper was to describe novel data visualisation techniques that address the limitations of current data presentation methods; and to offer future investigations an opportunity to explore and compare time-history data across segment couplings, multiple participants, repeated measures, and experimental conditions with ease and in a meaningful way with a focus on foot and ankle.

4.1 Coupling angle mapping

The vertical stacking of coupling angle maps using a colour scheme offers a distinction between individual coordination patterns. The advantage of this method is that it supports multiple single-subject research designs and a data analysis technique known as coordination profiling. Coordination profiling is a process where the participants from a small group perform multiple trials of a movement task in a repeated measures experimental design. It involves an in-depth analysis of how an individual uniquely performs a goal-oriented movement task and is used to highlight commonalities and differences between trials or individuals [5,31]. In the current study, coupling angle mapping visibly identified commonalities in coordination patterns across individuals in sagittal plane foot-shank coordination during loading response and the later stage of the propulsion phase (Fig. 3a). In addition, presenting colour within bar plots makes it easy to compare the time-history between trials or individuals concurrently at each instant in time, and clearly outlines subtle differences in the timing of transitions between coordination pattern classifications. In contrast, the overlaying of data points on a traditional coupling angle-time series figure would make it difficult from a qualitative perspective to gain the same conclusions on commonalities and transition points.

4.2 Segmental dominancy profiling

Another common way to analyse coupling angle data is through frequency analysis, which refers to a count on the number of the times the coupling angle is distributed within each coordination pattern classification over a normalised movement cycle. As an example, Figure 6b suggests sagittal plane foot-shank coordination during stance is predominately in-phase with proximal segment dominancy, which was also concluded from coupling angle mapping (Fig. 3b). However, categorising the coupling angle to frequency bar plots or using colour alone cannot describe the change in the distribution of the coupling angle within a coordination pattern classification over time. It is possible for example, to observe a 30-40° difference in the distribution of the coupling angle within a coordination pattern classification while the overall frequency count or coupling angle map would draw the same conclusions.

As stated in the methodology section, the dominancy of the proximal or distal segment during in-phase or anti-phase coordination can be quantified as a percentage by converting the coupling angle to gradian [8]. This study chose bar plots as a data visualisation technique to profile segmental dominancy in a time-domain. The segmental dominancy axis scale ranges from 50% to 100%, therefore, an increase or decrease in the height of each bar plot can describe the distribution of the coupling angle within a coordination pattern classification over time. Between 0% and 7% of stance for example (Fig. 3b), foot-shank coordination is in-phase with distal dominancy and there is a gradual decrease in distal segmental dominancy from 67% to 51%. This represents a gradual decrease in the coupling angle from 60° to 47°. Subsequently, there is a continual decrease in the coupling angle from 43° to 4° until 20% of stance that coincides with a gradual increase in the height of the bar plots as the proximal segment becomes more dominant (52% to 97%) even though the coordination pattern classification remains in-phase.

4.3 Inter-data point range of motion profiling

While the novel application of segmental dominancy profiling has been stated previously, the significance of each percentage can only be obtained if there is reference to segmental ROM. However, as it stands, vector coding can only provide information on the phase coordination between two segments. Recently, it has been shown that combining segment angles with coupling angle data on a time-series figure can provide a detailed interpretation of coupling angle and coordination variability data [8]. Yet overlaying segment angles on coupling angle maps would not make for an intuitive interpretation when the proposed data visualisation techniques are used for multiple single-subject analyses; since range of motion for several segments can be large (example Fig. 1b) and this would make it difficult to visualise the subtle changes in segment angles. Therefore, since segmental dominancy profiling relates to the dominant segment and that subtle changes in segment angles are regularly seen on angle-angle plots, the current study chosen to quantify IDP-ROM of the dominant segment. Combining coupling angle mapping with segmental dominancy and IDP-ROM profiling now provides an in-depth analysis of patterns of coordination and patterns of control between two segments. Indeed, a better understanding of patterns of coordination and patterns of control may assist in the characterisation of efficient and effective movement techniques that describes clearly on how performance outcomes were achieved [35]. On foot-shank coordination in the sagittal plane for example (Fig. 3b), greater IDP-ROM is noted towards the end of stance and this is expected as this relates to a rapid transition from peak dorsi-flexion to peak plantar flexion (78-100% of stance). In addition, both segments are rotating in the same direction during this phase of stance (dark red colour), but it is the foot (distal segment) that is progressively contributing more to plantar flexion at the ankle joint than the shank (proximal segment). This is shown by a progressive increase in segmental dominancy and IDP-ROM profiles. In another example (Fig. 3b), there is a rapid increase in proximal dominancy between 10-20% of stance although IDP-ROM progressively reduces. Again, this is expected since the shank segment progresses forward over the foot and contributes more to dorsi-flexion at the ankle joint through mid-stance until the heel begins to raise off the floor. In contrast, multiple single-subject analyses using coupling angle mapping reveals subtle deviations in the coordination pattern in comparison to the group observation described above (Fig. 3f).

4.4 Coordination variability mapping and profiling

A spectrum of colours was chosen to map the degree of coordination variability that offers an opportunity to visually inspect an entire dataset for potential regions of interest that would be hidden through group analysis (i.e. a dark red colour indicates very high coordination variability). However, one could argue that it can be visually challenging to detect the change in the degree of variability using colour alone. Therefore, data-bars represent the same data used for colour mapping but provide better visualisation and profile of coordination variability across a movement cycle.

There is increasing evidence that coordination variability reveals valuable information on changes in movement strategies [6,36]. Low coordination variability for group foot-shank coordination in the sagittal plane is explained by the similarities in the coordination pattern time-history of several participants in comparison to the group observation, and that transitions between classifications relate to a change in segmental dominancy while the phase coordination between segments remained in-phase (Fig. 3f) . In comparison, the high degree of coordination variability noted during stance for group rearfoot-forefoot coordination in the frontal plane could be explained by the distribution of the coupling angle across multiple coordination pattern classifications (Fig. 3e). This suggestion is supported by previous findings that revealed high coordination variability occurs most notably during the transition between in-phase and anti-phase coordination or vice-versa [6,37]. However, it has been recently shown that when circular statistics are used to calculate coordination variability, shorter vector lengths and a closer proximity of adjacent data points as indicated by low IDP-ROM values, can create a statistical artefact that increases coordination variability values [38]. Nevertheless, subtle differences between individuals regarding the coordination pattern strategies, the timing on the transition between coordination patterns, and low IDP-ROM, explains why group data in comparison to participant data is higher and for an extended period (Fig 3e).

4.5 Data analysis consideration

Current approaches to reporting vector coding data usually involve dividing a movement of interest into phases that are defined by functional events [27,30,46]. For each phase the mean coupling angle and/or mean coordination variability is calculated from a set number of trials, and these discrete values represent the coordination pattern or coordination variability between the respective two segments. However, as shown in the current study, the mean coupling angle can span within and between coordination pattern classifications during a phase of a movement. This question the applied use of the mean coupling angle and mean coordination variability data to inform interventions. Moreover, with such discrete measures, it is not possible to identify the link between the reported dependent variable and the actual movement in a time domain.

4.6 Practical application

While the spectrum over three colours was selected in the current study to depict the degree of variability between 0° and 80°, additional colours could be used in various movement scenario's to define specific variability thresholds. In a clinical setting for example, it is proposed that low coordination variability limits the ability to call upon alternative coordinative strategies that may result in cumulative stress on soft tissues, which over time may be a factor associated with an overuse injury [39]. Although there is increasing evidence [40–43] to support the development of a coordination variability continuum [39], a coordination variability threshold that can be linked to pathology is yet to be identified. The mapping and profiling of coordination variability of a dataset representing multiple single-subject analyses can be used to identify commonalities in the degree of coordination variability between healthy and individuals with pathologies.

Increasingly, practitioners are adopting a constraints-led approach and an understanding of coordination variability to direct rehabilitation and exercise prescription. Dingenen et al. [44] provide an applied summary of the relationship between variability in coordination strategies during preferred movements, and variability based on environmental constraints. For example, if the variability of the environmental constraint is high, it is advantageous to display high variability in coordination pattern strategies to allow adaptations to the everchanging environment; whereas exhibiting high variability in coordination patterns where environment variability is low would suggest inefficient performance [44]. On this understanding, instead of asking patients to repeat the same goal-orientated movement to achieve some form of consistency that may be considered ‘normal’, practitioners should encourage individuals to perform a variety of movement competencies to challenge coordination pattern availability [44–47]. Since coordination patterns are unique to each individual an essential part of evidenced-based rehabilitation is attention towards individual patients [20,44]. However, in a clinical population, it can be argued that obtaining a homogeneous sample to allow for comparison between groups or to examine the effectiveness of an intervention is extremely difficult if not impossible. In general, group-based research design studies complimented with multiple single-subject analyses has undoubtedly clear implications for musculoskeletal health [13,15]. The application of the data visualisation techniques proposed in the current study can support both multiple single-subject analyses (Fig. 3e/4a) and individual case studies (Fig. 5).

5. Conclusions

The use of colour mapping profiling techniques highlighted differences in the coordination pattern and coordination variability across several participants that questions the interpretation and relevance of reporting group data. The use of colour and data bars to map and profile information on segment couplings offers an opportunity to explore an entire dataset. With the capability of displaying coordination pattern and coordination variability data with ease across multiple participants and repeated measures, colour mapping is a reporting technique that can assist current data analysis techniques (i.e. coordination profiling, multiple single-subject analysis, case studies and analysis of reliability), and proposed theories on overuse injuries and rehabilitation strategies. The use of data bars details segmental dominancy that offers an intuitive visual on coupling angle distribution. The novel inclusion of IDP-ROM now provides a meaningful interpretation of segmental dominancy data and details patterns of movement control. Overall, the data reporting techniques outlined to support vector coding can have significant implications in biomechanics and analysis of human movement.

Conflictofinterestfor statemnet

All authors were fully involved in the study and preparation of the manuscript and declare that there is no conflict of interest.

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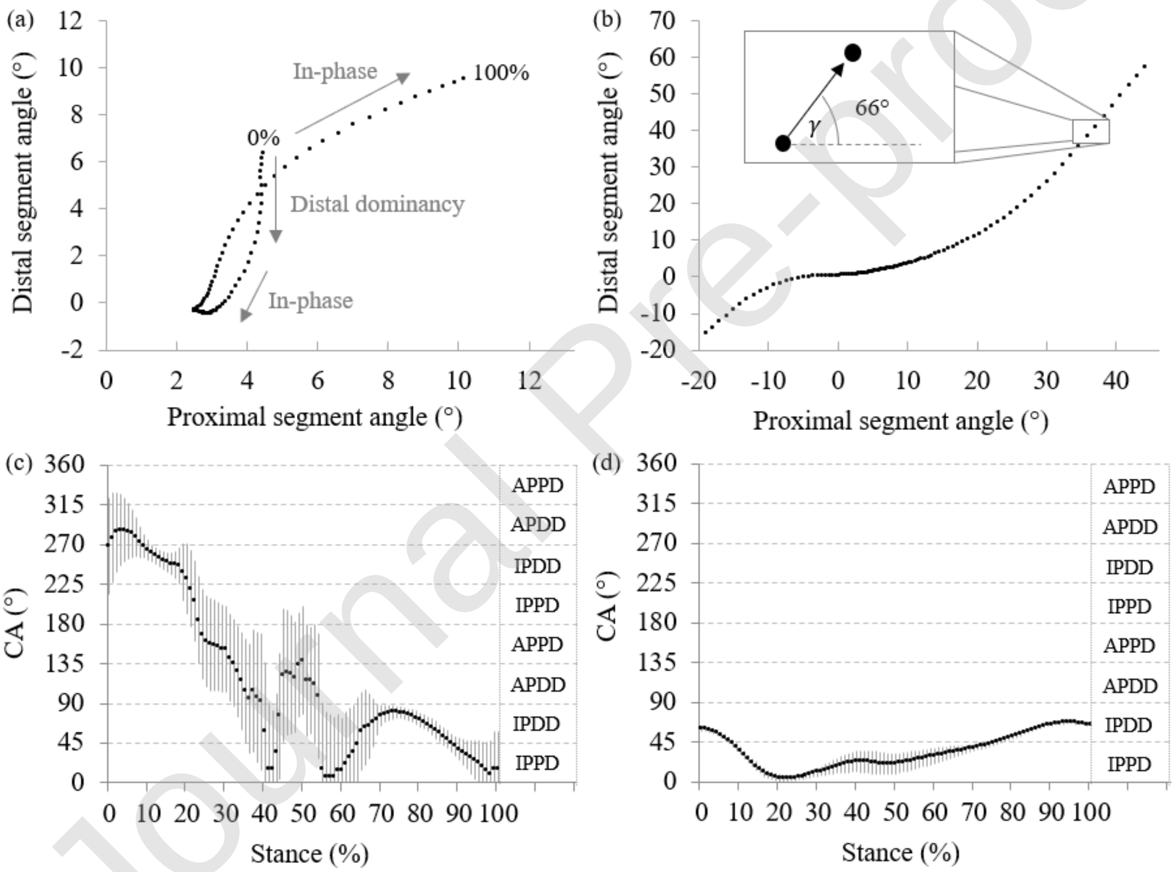
List of Figures

Fig. 1. (a) Angle–angle diagram of forefoot (distal) – rearfoot (proximal) coordination during stance in the frontal plane; (b) Angle–angle diagram of foot (distal) – shank (proximal) coordination during stance in the sagittal plane. Both figures represent mean data from 10 participants; (c) Mean coupling angle data on forefoot–rearfoot coordination during stance in the frontal plane; (d) foot–shank coordination during stance in the sagittal plane. Coupling angle data lies within a row that represents the associated coordination pattern classification (IPPD-in-phase proximal dominancy, IPDD-in-phase distal dominancy, APPD-anti-phase proximal dominancy, APDD-anti-phase distal dominancy). Vertical grey lines representation coordination variability; (e) Individual coupling angle data on forefoot–rearfoot coordination during stance in the frontal plane; (f) Individual coupling angle data on foot–shank coordination during stance in the sagittal plane; (g) Individual coordination variability data on forefoot–rearfoot coordination during stance in the frontal plane; (h) Individual coordination variability data on foot–shank coordination during stance in the sagittal plane.



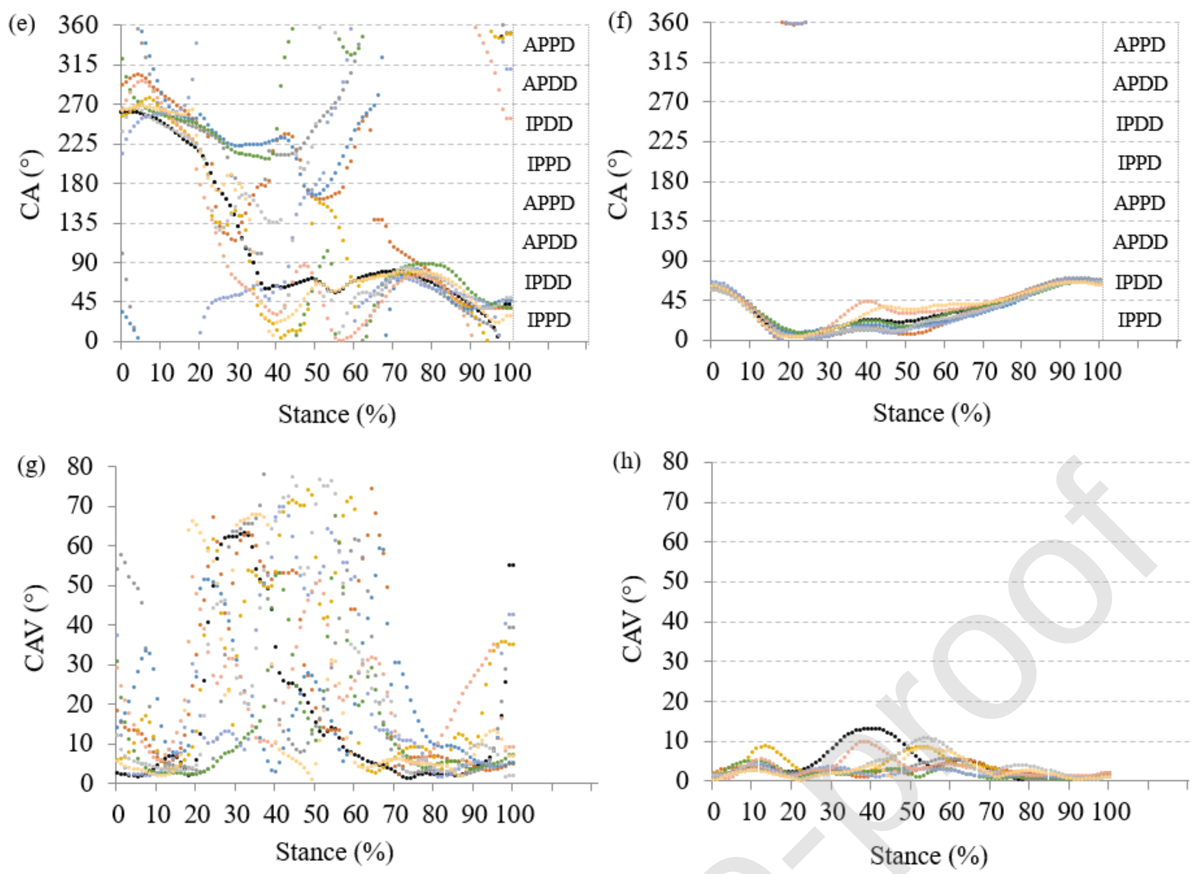


Figure 1a-h.

Fig. 2. Coordination pattern classification proposed by Needham et al.[8] illustrating colour-scale for each classification. Segmental dominancy (%) is shown around the circumference of the polar plot (grey text, D-distal / P-Proximal).

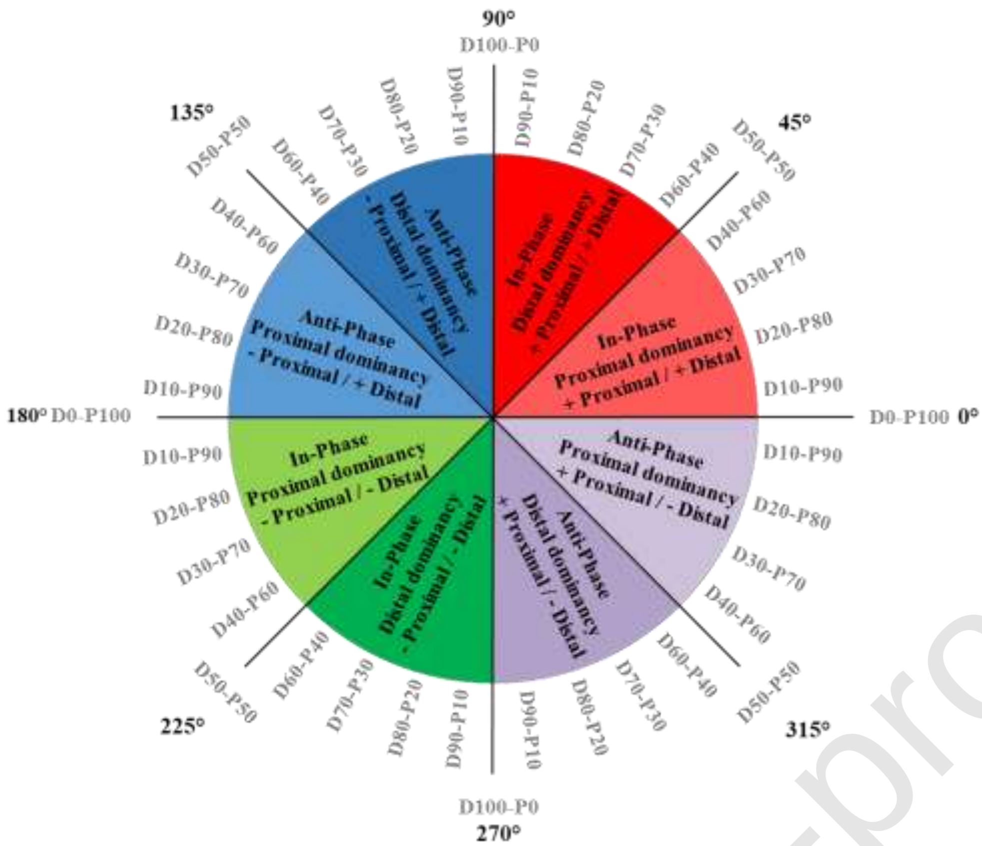
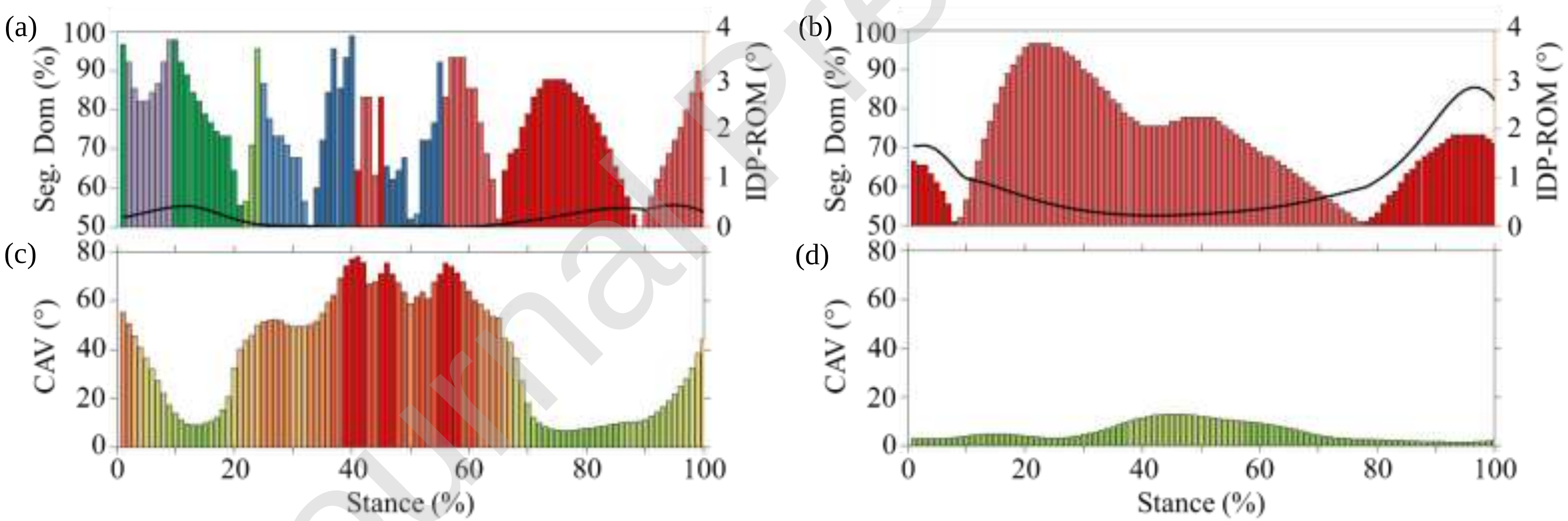

90°
D100-P0
45°
135°
180° D0-P100
D0-P100 0°
225°
315°
D100-P0
270°
In-Phase
Distal dominancy
+ Proximal / + Distal
In-Phase
Proximal dominancy
+ Proximal / + Distal
Anti-Phase
Distal dominancy
- Proximal / + Distal
Anti-Phase
Proximal dominancy
- Proximal / + Distal
In-Phase
Proximal dominancy
- Proximal / - Distal
In-Phase
Distal dominancy
- Proximal / - Distal
Anti-Phase
Distal dominancy
+ Proximal / - Distal
Anti-Phase
Proximal dominancy
+ Proximal / - Distal
D90-P10
D80-P20
D70-P30
D60-P40
D50-P50
D40-P60
D30-P70
D20-P80
D10-P90

Figure 2.

Fig. 3. (a-b) Coupling angle mapping, segmental dominancy and IDP-ROM profiling representing mean forefoot–rearfoot coordination during stance in the frontal plane and foot–shank coordination during stance in the sagittal plane, respectively (See Fig. 2 for colour-scale legend); (c-d) coordination variability mapping and profiling on forefoot–rearfoot coordination during stance in the frontal plane and foot–shank coordination during stance in the sagittal plane, respectively; (e-f) Coupling angle mapping, segmental dominancy and IDP-ROM profiling illustrating on forefoot–rearfoot coordination during stance in the frontal plane and foot–shank coordination during stance in the sagittal plane, respectively for 10 participants (P1-P10) and for the group coupling angle (MCA) and group coordination variability (MCAV). <u>For visualisation purposes, the measurement scale for IDP-ROM (right vertical axis) in Figures e and f are 0-1° and 0-4°, respectively.</u> Figures are time-series matched.



(e)

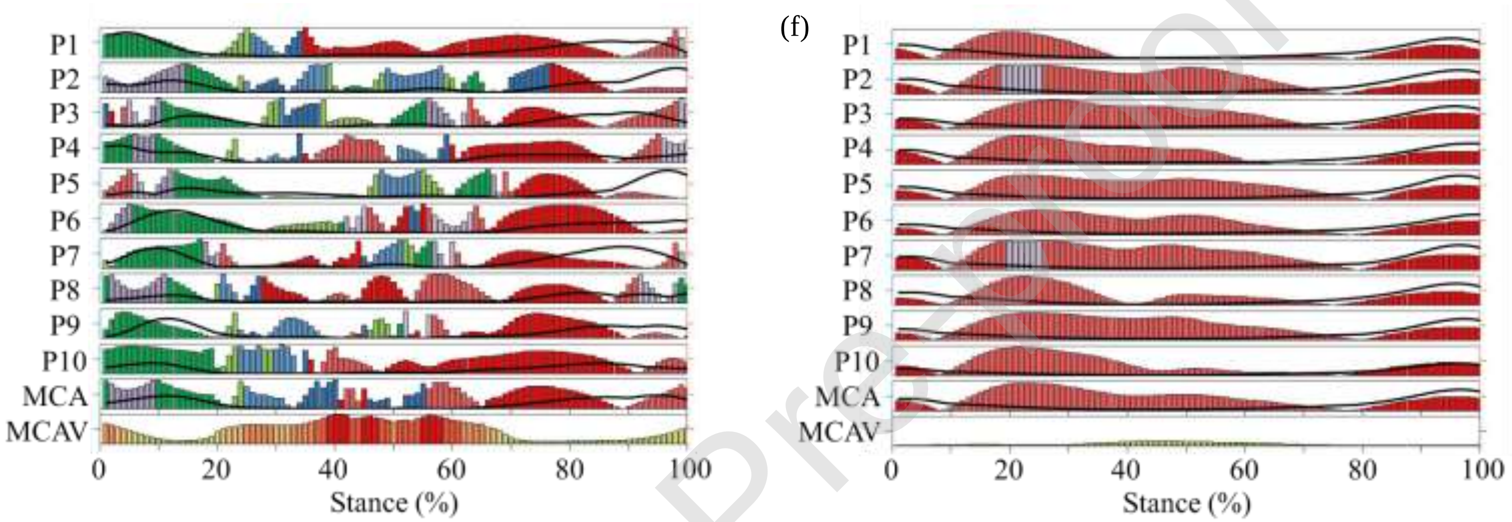


Figure 3.

Fig. 4. (a-b) Coordination variability mapping and profiling on forefoot–rearfoot coordination during stance in the frontal plane and foot–shank coordination during stance in the sagittal plane, respectively for 10 participants (P1-P10) and for the group coordination variability (MCAV).

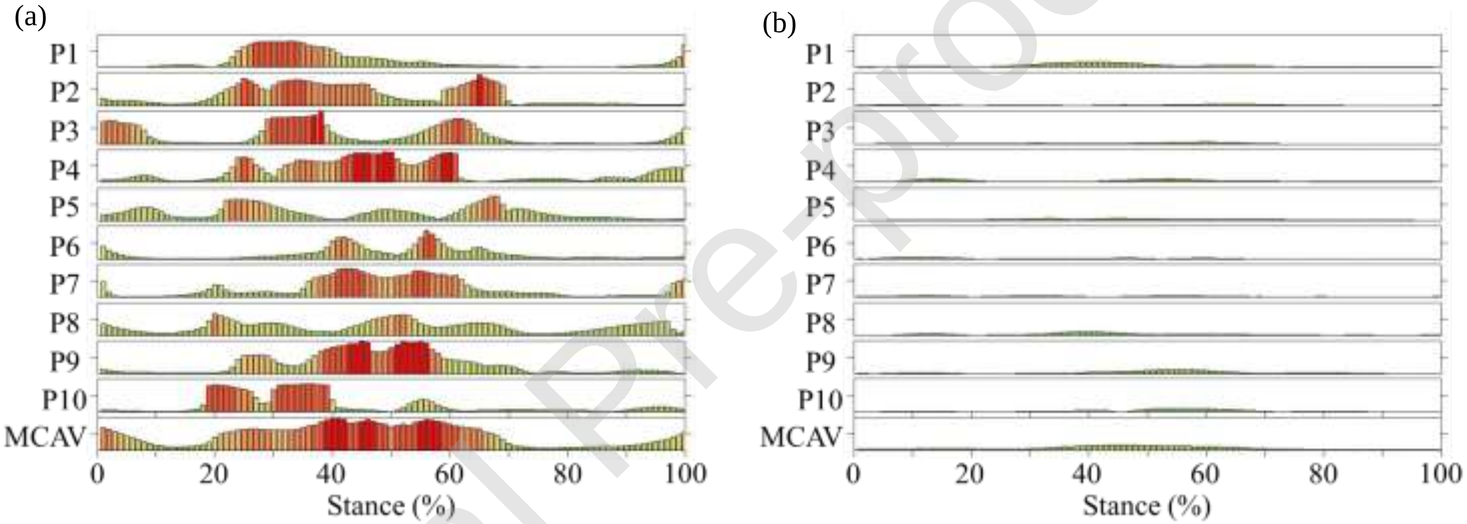


Figure 4.

Fig. 5. Coupling angle mapping, segmental dominancy and IDP-ROM profiling representing mean and individual trial data for a single participant (forefoot–rearfoot coordination during stance in the frontal plane).

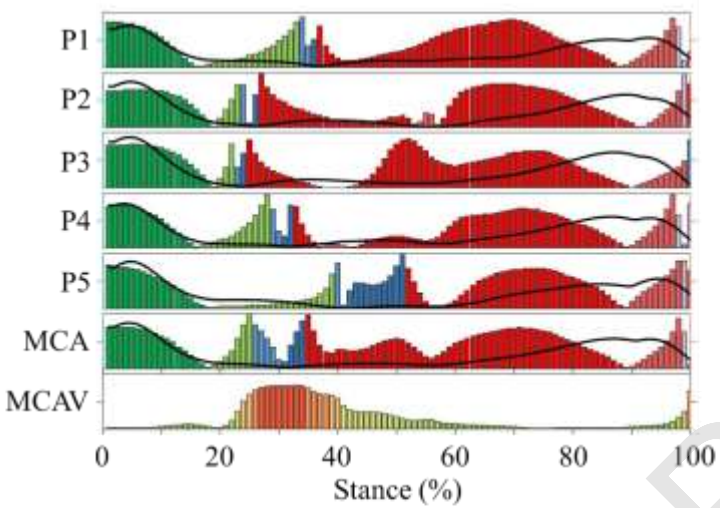


Figure 5.

Fig. 6. (a-b) Coordination pattern frequency data on forefoot–rearfoot coordination during stance in the frontal plane and foot–shank coordination during stance in the sagittal plane, respectively.

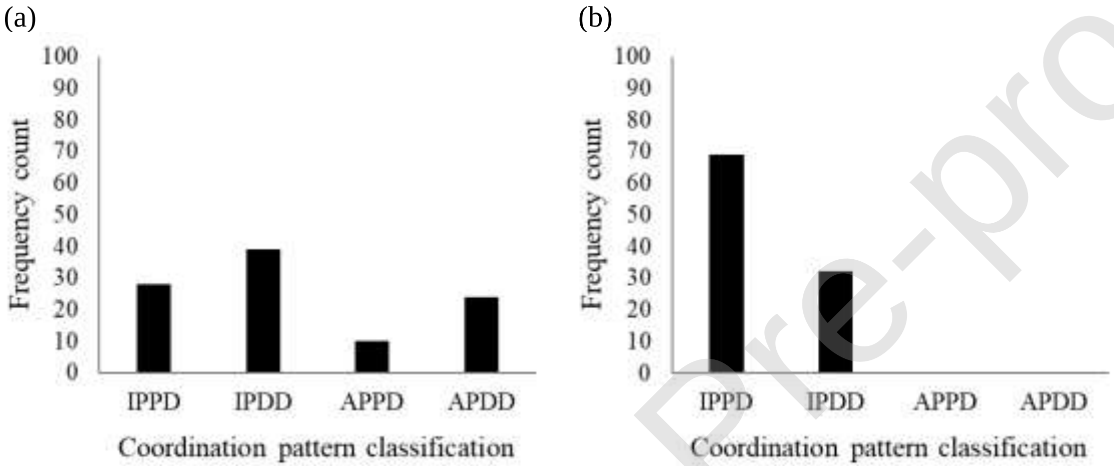

(a)
Frequency count
100
90
80
70
60
50
40
30
20
10
0
IPPD
IPDD
APPD
APDD
Coordination pattern classification
(b)
Frequency count
100
90
80
70
60
50
40
30
20
10
0
IPPD
IPDD
APPD
APDD
Coordination pattern classification

Figure 6.