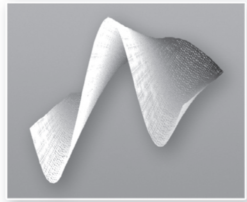

Chapter 9

Measuring Coordination and Variability in Coordination

Jonathan S. Wheat, PhD, and Paul S. Glazier, PhD

Editors' Overview

This chapter reviews tools for measuring movement coordination and its variability and draws attention to the capacity of enhanced technology in motion analysis for providing detailed measurements of the coordination among limb segments and joints of the body. The review is highly relevant for theorists of motor control interested in measuring movement coordination and its variability during complex actions with multiple degrees of freedom such as locomotion. Key differences in methodological assumptions in the literature on biomechanics and motor control are identified, such as in assumptions regarding the definition of phase angle used when describing coordination between two segments. Decisions in measurement protocol, such as whether conventional linear statistics or circular statistical techniques should be used, can greatly influence the level of variability found in coordination. Although the literature is currently focusing a lot of attention on continuous relative phase and vector coding techniques, no single ideal technique exists for measuring coordination and its variability over time. Consequently, researchers need to be aware of the strengths and limitations of existing methods and should state the rationale for using particular methodologies in their research studies to help readers interpret what amount of variability in the data is likely due to measurement errors and discrepancies. Measuring coordination and its variability is an issue that continues to challenge researchers in the movement sciences.

As Glazier, Wheat, Pease, and Bartlett highlighted in chapter 3, traditionally in biomechanics, data from isolated joints (e.g., displacement, velocity, angle, force, and so on) are presented as a function of time, with much research focusing on the relative timing and magnitude of time-discrete kinematic variables. Glazier and colleagues drew attention to studies that have investigated the coordination between joints and body segments. It has recently been suggested that the coordination or coupling relationships between segments may be an important line of investigation owing to the fact that motor behaviors may be distinguished by the coordination between entire limbs and body segments (Tepavac and Field-Fote, 2001). Also, the coordination between adjacent anatomical structures, such as the subtalar and knee joints, has been implicated in the etiology of injuries (e.g., Lafortune, Cavanagh, Sommer and Kalenak, 1994; McClay and Manal, 1997; Stergiou and Bates, 1997; Nawoczenski, Saltzman and Cook, 1998; Stergiou, Bates and James, 1999). However, quantifying the coordination between two body segments is problematic. In this chapter we outline, from a biomechanical perspective, various techniques that are commonly used in research on motor control in order to measure coordination and, arguably more importantly, variability in coordination. We also highlight the major benefits and limitations of these methods.

Measuring Coordination and Variability in Coordination

In the late 1960s, Grieve (1968, 1969) proposed that the angular time series of two joints be plotted against each other on what was called a relative motion plot. These plots, also known as angle–angle diagrams, have since been used to distinguish normal and pathological gait (Hershler and Milner, 1980; Miller, 1981; Charteris, 1982), compare symmetrical and asymmetrical gait (Whitall and Caldwell, 1992), identify differences between same-field and opposite-field hitting in baseball players of different expertise (McIntyre and Pfautsch, 1982), and examine changes in coordination during the practice of a soccer kick (Anderson and Sidaway, 1994). However, as Tepavac and Field-Fote (2001) highlighted, angle–angle diagrams are excellent for qualitative purposes but quantifying the data can be problematic. Parenthetically, the problem of how to quantify the coordination between body segments is effectively the same as of how to quantify the data in an angle–angle diagram. Many techniques have emerged to quantitatively evaluate the coordination or coupling between body segments, including discrete relative phase (van Emmerik and Wagenaar, 1996; LaFiandra, Wagenaar, Holt and Obusek, 2003), continuous relative phase (Hamill, van Emmerik, Heiderscheit, and Li, 1999; Heiderscheit, Hamill and van Emmerik, 1999; Post, Daffertshofer and Beek, 2000; van Uden, Bloo, Kooloos, van Kampen, de Witte and Wagenaar, 2003), vector coding techniques (Whiting and Zernicke, 1982; Sparrow, Donovan, van Emmerik, and Barry, 1987; Tepavac and Field-Fote, 2001; Heiderscheit, Hamill, and van Emmerik, 2002), and other techniques such as cross-correlation (Amblard, Assaiante, Lekhel, and Marchland, 1994) and normalized root mean squared difference (Sidaway, Heise, and Schoenfelder-Zohdi, 1995). In the following sections we review these techniques, focusing mainly on methods of relative phase and vector coding, and we discuss their relative merits and limitations in quantifying coordination and variability in coordination.

Relative Phase

Both discrete relative phase (DRP) and continuous relative phase (CRP) are based on the assumptions that the two oscillating segments under scrutiny are of a one-to-one frequency ratio and they exhibit a sinusoidal time history (Hamill et al., 2000). Clearly, segmental motions in gait and sport do not always meet these assumptions, and problems can arise when using relative phase to quantify the coordination between body segments in such activities. Care should therefore be taken when interpreting data on relative phase in relation to intersegment coordination, especially if these assumptions are violated. However, alternative techniques are available, such as relative Fourier phase (Lamoth, Beek, and Meijer, 2002, see the section "Continuous Relative Phase"), to transform the data and ensure that they satisfy the assumptions.

Discrete Relative Phase DRP is a point estimate that illustrates the latency of an event in the motion of a segment with respect to the motion of another segment (Kelso, 1995). When the relative timing of the events between two segments is important, as in investigating the relationship between subtalar inversion-eversion and knee flexion-extension (Lafortune et al., 1994; McClay and Manal, 1997; Stergiou and Bates, 1997; Nawoczenski et al., 1998; Stergiou et al., 1999), DRP may be an important variable. DRP has already been used to measure the phase difference between thoracic and pelvic rotations during treadmill walking (Lamoth et al., 2002), determine the effect of load carriage on trunk coordination (La Fiandra et al., 2003), and examine the transition between walking and running in human locomotion (Diedrich and Warren, 1995). DRP can be calculated using the following equation:

$$\Phi = \frac{t_{\max\varphi 1(j)} - t_{\max\varphi 2(j)}}{t_{\max\varphi 1(j+1)} - t_{\max\varphi 1(j)}} \times 360^\circ$$

In this equation, *t* is time, *max*φ*1* is the maximum rotation of segment 1, *max*φ2 is the maximum rotation of segment 2, and φ is the phase difference during the cycle *j*.

Hamill et al. (2000) suggested that, when considering the example of knee flexion-extension and subtalar inversion-eversion, in which it might be appropriate to study the stance phase in isolation, foot strike could be used as the initial point of the cycle. They also suggested that the length of the stance phase could represent the time of the cycle. Therefore, in this example *max*φ*1* is maximum subtalar eversion, *max*φ2 is maximum knee flexion, and the period of time (the denominator) is simply the duration of the stance.

Since DRP is calculated in the range of $0^\circ \leq \varphi \leq 360^\circ$ and there is redundancy in the angles (e.g., 0° and 360° are equivalent), DRP is a circular variable. Therefore, to avoid phase wrapping (Burgess-Limerick, Abernethy, and Neal, 1991; Lamoth et al., 2002), the average DRP over several cycles and the variability of coordination should be calculated using circular statistics (see Batschelet, 1981 or Mardia, 1971 for an overview).

One advantage of DRP is that it requires no further manipulation of the data other than what is normally carried out in the calculation of joint angles (Hamill et al., 2000). However, problems may arise if the data do not meet the assumptions of having sinusoidal time histories and a one-to-one frequency ratio. There would certainly be a problem if definite peak values could not be ascertained or respective peak values changed between cycles. In other words, patterns of angular displacement that contain multiple maxima and minima might impede the calculation of DRP if the magnitudes of the peaks changed from cycle to cycle, so that selecting a peak in each cycle that correctly corresponds to peaks in other cycles is difficult. This phenomenon would be most detrimental to calculating variability in coordination, as erroneously high variability may be calculated simply because the magnitudes of the separate peaks change between each cycle. Changes in respective peak values are not a problem in most of the examples from the literature on coordination cited earlier in this section. They might become a problem if DRP is used to analyze other sport techniques or joint motions with more peaks and troughs in the time series of angular displacement. Changes in the magnitudes of the peaks from cycle-to-cycle might introduce ambiguity into the definition of the required peak value. Another obvious disadvantage is that DRP provides only one measurement per cycle of movement.

Continuous Relative Phase CRP indicates the phase relation between two oscillating segments at each sampled data point throughout the cycle of movement. Both CRP and variability in CRP have been used to examine running injuries (Hamill et al., 1999; Heiderscheit et al., 1999), the coordination of finger oscillations (Kelso, 1981, 1984), the coordination of thorax and pelvis rotations (van Emmerik and Wagenaar, 1996; Lamoth et al., 2002; LaFiandra et al., 2003), patterns of coordination in walking and running (Li, van den Bogert, Caldwell, van Emmerik and Hamill, 1999), one-legged hopping (van Uden et al., 2003), and intralimb coordination following obstacle clearance (Stergiou, Scholten, Jensen and Blanke, 2001a; Stergiou, Jensen, Bates, Scholten and Tzetzis, 2001b). The CRP between two oscillating segments at any given instant is defined as the difference between the respective phase angles of each segment. Hamill et al. (2000) recently highlighted that before CRP can be calculated, the displacements and velocities of the segments need to be normalized to eliminate the effects of differences in the amplitudes of the range of motion of each segment—this issue is discussed later in this section. Also, the data on displacement and velocity should be interpolated to a fixed number of data points so that ensemble averages and variability can be calculated. These displacement and velocity data are then used to construct a phase-plane portrait (normalized angular velocity versus normalized angular displacement) for each segment; a typical phase-plane portrait is illustrated in figure 9.1. Phase-plane portraits graphically represent all possible states of the segment (Clark, 1995), as the behavior of a dynamic system may be captured by a variable and its first derivative with respect to time (Rosen, 1970).

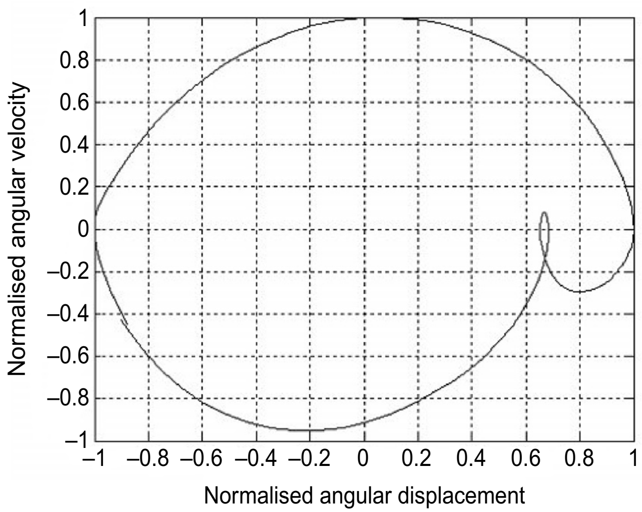

FIGURE 9.1 An example of a phase-plane portrait for hip flexion-extension.

The Cartesian coordinates of each data point on the phase plane are then converted to polar coordinates. The phase angle component is given by the following equation:

$$\varphi(t) = \tan^{-1}\left(\frac{\dot{\theta}(t)}{\theta(t)}\right)$$

In this equation, $\dot{\theta}$ is normalized angular velocity, θ is the normalized angular displacement, and φ is the phase angle at time *t*.

The CRP between the two segments can be calculated as the difference between their phase angles, which is usually achieved by subtracting the phase angle of the distal segment from that of the proximal segment. For example, the CRP between the shank and the foot during running is calculated using the following equation:

$$\Phi(t) = \varphi_{shank}(t) - \varphi_{foot}(t)$$

In this equation, φ_{shank} is the phase angle of the shank, φ_{foot} is the phase angle of the foot, and φ is the CRP at time *t*.

In calculating the component phase angle, the output of $\tan^{-1}(y/x)$ takes on values between –90° and +90°. Therefore, the output data need manipulating to ensure that the component phase angles are calculated within a suitable range. In the literature on studies using CRP, a discrepancy exists in the definition of the range of component phase angle used. In motor control (see Scholz, 1990 for an overview), a range of 0° ≤ φ ≤ 360° has typically been used, but the recent application of this technique in biomechanics has brought with it a new range of 0° ≤ φ ≤ 180°. Hamill et al. (2000) suggested that this new range is necessary because there is redundancy in the angles in the original range (0° and 360° mean the same thing). Presumably, this new definition is preferred because it avoids discontinuities in the component phase angles, which can be problematic if conventional linear statistical analyses are used.

Changes in the definitions of the component phase angle, however, affect the values of the computed CRP. Wheat, Bartlett, and Milner (2003) investigated the effect of using different definitions of component phase angles on CRP. In this study, test data were created for two segments using sine and cosine functions. Data from a sine function served as the angular displacement of one segment. Similarly, as cosine is the first derivative of sine, data from a cosine function served as the angular velocity of the same segment. The CRP of the two segments was manipulated by adding a given amount to the angles inputted into the sine and cosine functions for the second segment. Three conditions were tested in which the segments were 180°, 90°, and 45° out of phase. In the 180° out-of-phase conditions, constant CRP values that instantaneously switched between 180° and –180° (which effectively mean the same thing) were apparent for the range of 0° ≤ φ ≤ 360°, but they were not evident when the phase angles were defined in a range of 0° ≤ φ ≤ 180° (figure 9.2). Instead, a gradual shift between 180° and –180° was seen. Similar results were obtained for the 90° and 45° out-of-phase conditions.

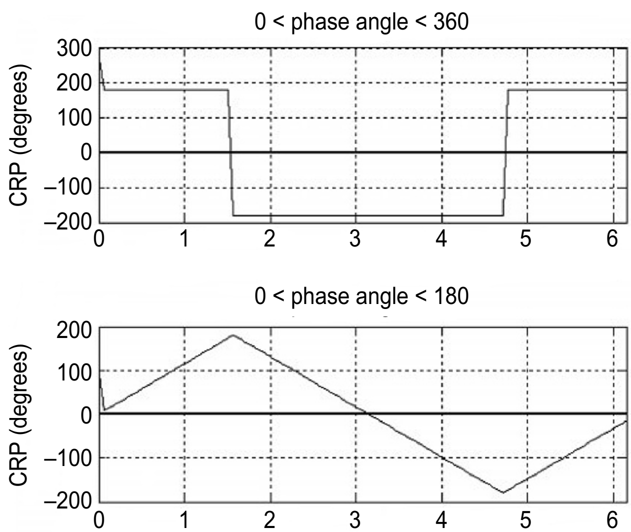

FIGURE 9.2 Continuous relative phase calculated with two different definitions of component phase angle.

It appears that if information about the coordination between segments is required, the range of 0° ≤ φ ≤ 360° is most suitable because the range of 0° ≤ φ ≤ 180° does not yield correct results. In other words, if Kelso had used the range of 0° ≤ φ ≤ 180° in his work monitoring nonlinear phase transitions in finger movement, he would never have been able to record the antiphase (±180° out-of-phase) relationship. Recently, other ranges have also been used, including –180° ≤ φ ≤ 180° (e.g., Lamoth et al., 2002), which is effectively the same as 0° ≤ φ ≤ 360°, and 0° ≤ φ ≤ 90° (e.g., Kurz and Stergiou, 2002), which has the same problems as 0° ≤ φ ≤ 180°. As already suggested, presumably the definition of 0° ≤ φ ≤ 180° (and 0° ≤ φ ≤ 90°) was used to avoid the discontinuities in the component phase angles and, subsequently, in the CRP data during the analysis of most movements. These discontinuities can introduce anomalies that may cause erroneously high variability with conventional linear statistical techniques. However, this problem is easily solved if the recommended circular statistical techniques are used (see Burgess-Limerick et al., 1991; Lamoth et al., 2002). If researchers wish to present CRP data graphically as a function of time but do not want to present data containing discontinuities, they should manipulate CRP data to a suitable range after calculation, as Lamoth et al. (2002) have done. However, care should be taken to maintain any lead-lag information in the data. Authors should certainly state their definitions of phase angle so the reader can make an informed and correct interpretation of the results (Wheat et al., 2003).

As mentioned previously, the need to normalize the data in a phase-plane portrait has been identified (e.g., Hamill et al., 2000). Normalization adjusts for amplitude differences in the ranges of motion and centers the phase-plane portraits about the origin (Hamill et al., 2000; Lamoth et al., 2002). Hamill et al. (2000) presented data highlighting the effects of different normalization techniques on CRP and variability in CRP. Differences were seen in both CRP and variability in CRP among the four techniques discussed. The authors suggested that ultimately the choice of a normalization procedure will likely depend on specific aspects of the research question. Conversely, Kurz and Stergiou (2002) suggested that normalization is not required when calculating component phase angles. They investigated the effects of three different conditions of normalization—two normalization techniques and no normalization—on calculating phase angles within two different ranges, which appear to be 0° ≤ φ ≤ 180° and 0° ≤ φ ≤ 90°. They suggested that certain combinations of parameters produced "errors" in the calculated CRP. They proposed that normalizing the data on a phase plane is not required because of the properties of the arctangent used in calculating the component phase angles. They suggested that CRP is not affected by differences in amplitude between segments since the arctangent is based on a ratio (velocity / displacement) and the differences in amplitude are removed during the calculation of phase angle (Kurz and Stergiou, 2002). However, Peters, Haddad, Heiderscheit, van Emmerick, and Hamill (2003) used distorted sine waves with a known phase relationship to present data that suggested that calculating CRP without normalizing the data on a phase plane produced erroneous results. Even when two sine waves with a frequency other than 0.5 / π were tested, incorrect CRP values were obtained without normalization. Another reason for normalizing the data on a phase plane is to center the trajectory on the origin (Hamill et al., 2000). In their analysis, Kurz and Stergiou (2002) used phase angle definitions of $0° \leq \varphi \leq 180°$ and $0° \leq \varphi \leq 90°$, which have been shown to produce questionable CRP results (Wheat et al., 2003). Additionally, not normalizing the data affects the variability of CRP. As Heiderscheit (2000) indicated when highlighting the reasons why nonsinusoidal data affect variability in CRP, the proximity of a data point to the origin of the phase plane can directly influence the calculated variability in coordination. Two data points at a fixed distance exhibit a greater difference in phase angle the closer they are to the origin of the phase plane (figure 9.3). This suggests that when the data on phase planes are not normalized, erroneously high variability is observed in segments with small amplitudes. More work using both circular statistics and suitable definitions of component phase angle is required to determine the effects of different normalization techniques on calculations of CRP and variability in CRP.

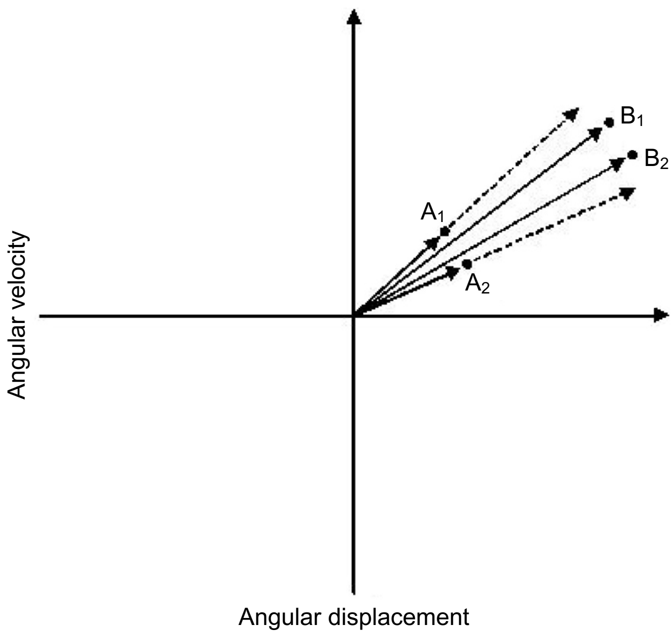

FIGURE 9.3 Data points are influenced by their proximity to the origin. Data points A_1 and A_2 have a greater difference in phase angle than do data points B_1 and B_2, even though the points in each pair are the same distance apart.
Adapted from Heiderscheit 2000.

CRP has many advantages in quantifying both coordination and variability in coordination. First, because angular velocity is included in the calculation of the component phase angles, CRP contains temporal - in addition to spatial - information (Hamill et al., 1999; Hamill et al., 2000), which gives a higher-dimensional and more detailed analysis of the behavior (Hamill et al., 1999). Additionally, the angular velocity may make CRP a more sensitive measurement of variability in coordination (Wheat, Mullineaux, Bartlett and Milner, 2002) than other techniques. However, a higher derivative (angular velocity) in the calculation propagates any errors—whether they are due to movement of the skin marker, to the recording system, or to any other source—in the displacement data. It may also introduce a greater error into the CRP data, which may then be interpreted as increased variability. Several authors (Burgess-Limerick et al., 1991; Stergiou et al., 2001a) have reported that CRP is advantageous since there is evidence suggesting that receptors exist within muscles and tendons that control both the position and velocity of the respective body segment (McCloskey 1978). Finally, another advantage of CRP is that it continuously measures coordination and variability in coordination throughout the entire movement. CRP and variability in CRP can therefore be calculated for different phases of the gait cycle for example (Hamill et al., 1999; Heiderscheit et al., 1999; Stergiou et al., 2001a; Stergiou et al., 2001b). This is particularly useful because of changing functional demands on the lower extremity throughout the stride cycle (Heiderscheit et al., 2002).

There are also limitations to calculating CRP. A fundamental limitation is the assumption that the time histories of the joint motions are sinusoidal. Clearly, this is not the case for some joint motions during some activities. However, in some cases centering the phase-plane trajectory on the origin by using a normalization procedure makes the time histories more suitable. As mentioned previously, the issue of whether or not the data on a phase plane need normalizing is a contentious one and requires further clarification. Also, there are techniques that effectively transform the data so that they have a more sinusoidal time history. Relative Fourier phase, for example, essentially transforms the data into the frequency domain and discards any frequencies other than the fundamental frequency. When the data are reconstructed in the time domain, the displacement trace is sinusoidal and CRP calculations can be conducted. In their study on coordination between the pelvic and thorax during pathological walking, Lamoth et al. (2002) justified this approach because "movements of the pelvis are affected by forceful contacts between the feet and the support surface . . . which induce oscillations affecting the phase progression of the pelvis rotation" (p. 112). In other words, Lamoth et al. were arguing that oscillations other than those at the fundamental frequency are not relevant to the coordination of the pelvis and thorax. However, when applying this technique to other coordinative structures, care should be taken to not disregard potentially relevant information. Another possible problem with CRP that has been raised by other authors (Tepavac and Field-Fote, 2001;

Mullineaux and Wheat, 2002) is that it is hard to relate to conceptually. This is mainly a problem for practitioners trying to interpret the type and nature of the relationship between joints and body segments. If the magnitude of variability in coordination is of interest, this is not so much of an issue.

Vector Coding Techniques

Numerous vector coding techniques have been introduced to quantify the data in relative motion plots and the variability in angle–angle trajectories (e.g., Whiting and Zernicke, 1982; Sparrow et al., 1987; Tepavac and Field-Fote, 2001; Heiderscheit et al., 2002). These techniques stem from the early work of Freeman (1961), who devised a chain-encoding technique to quantify an angle–angle curve. The procedure involves using a superimposed grid to transform the angle–angle trajectory into digital elements (see figure 9.4). Subsequently, a chain of digits that are based on the directions of the line segments formed by the frame-to-frame intervals between two consecutive data points is created. The chain of digits approximates the shape of the original analog curve. Integer chains from two different cycles are then cross-correlated to obtain a recognition coefficient, which is the peak value of the cross-correlation function. This technique has been used in studies of locomotion (Hershler and Milner, 1980; Whiting and Zernicke, 1982). However, as Tepavac and Field-Fote (2001) suggested, a flaw with this technique is that it converts data on the ratio scale to the nominal scale, risking the loss of important information and limiting the types of statistical analysis that can be applied. Also, a moti-

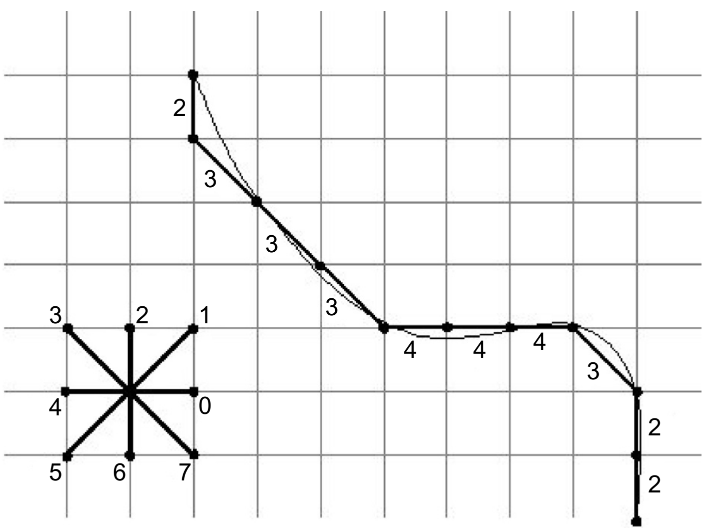

FIGURE 9.4 Freeman's (1961) chain-encoding technique.

vation behind Freeman's (1961) technique, computer efficiency, is no longer applicable owing to advances in computer hardware and software technology such as increased processor speeds and more sophisticated statistical analysis packages (Sparrow et al., 1987).

Another problem with this technique is that it requires the data points to be equally spaced. Sparrow et al. (1987) recognized that data are not always equally spaced in human movement and proposed a revised cross-correlation formula that takes into account the length of the frame-to-frame interval. However, Tepavac and Field-Fote (2001) identified two problems with the technique of Sparrow et al. (1987): (1) the two trajectories of interest must have an equal number of data points, and (2) it can only compare two trajectories at a time (multiple cycles must be compared in pairs).

Tepavac and Field-Fote (2001) revised the technique to address the above limitations. The authors presented a vector-based coding scheme that keeps data on a ratio scale for the quantification and analysis of relative motion. Field-Fote and Tepavac (2002) suggested that the technique provides an alternative to relative phase analysis, which was designed to help practitioners interpret the data, because these practitioners are more likely to think of movement in terms of joint angles and not phase values. In a way similar to that of Sparrow et al. (1987), Tepavac and Field-Fote (2001) identified the direction and magnitude of the frame-to-frame intervals on the angle–angle trajectories and calculated the magnitude and direction of the vector connecting the two points of the relative motion plot. However, as opposed to using pair-wise comparisons and cross-correlations, circular statistics were used to calculate the standard deviation of the direction of the vector at each frame-to-frame interval ($a_{i,\ i+1}$). This means that the variability in the angular component of the angle–angle trajectory can be calculated at each frame-to-frame interval for multiple cycles. The variability in the magnitude of the frame-to-frame vector was also calculated ($m_{i,\ i+1}$). Finally, the overall variability of the angle–angle trajectories was measured by simply finding the product of $a_{i,\ i+1}$ and $m_{i,\ i+1}$ ($r_{i,\ i+1}$) and was called the coefficient of correspondence. Field-Fote and Tepavac (2002) contended that this revised technique is mathematically equivalent to that of Sparrow et al. (1987). These three separate measurements mean that when using the vector coding algorithm (Tepavac and Field-Fote, 2001) it is possible to separately analyze a relative motion plot by its shape (angles, magnitude), the lengths of the frame-to-frame intervals, or the frame-to-frame vector deviation (a combination of shape and magnitude). Field-Fote and Tepavac (2002) used their vector coding technique to assess the consistency or variability of the coupling between the hip and knee in patients with incomplete spinal cord injury. These authors studied the patients over multiple cycles of treadmill walking performed both before and after a time of training. They used only the measurement of shape to assess variability, presumably because they thought changes in magnitude (changes in the range of motion at each joint from cycle to cycle) do not significantly affect the cycle-to-cycle variability relative to the shape changes in this population.

Both Hamill et al. (2000) and Heiderscheit et al. (2002) proposed subtle alternatives to the technique of Tepavac and Field-Fote (2001). These alternatives were presented as modifications to the method of Sparrow et al. (1987). In both techniques a coupling angle was defined as the orientation of the vector (relative to the right horizontal) between two adjacent points on the angle–angle plot (see figure 9.5). This is similar to the measurement of shape by Tepavac and Field-Fote (2001).

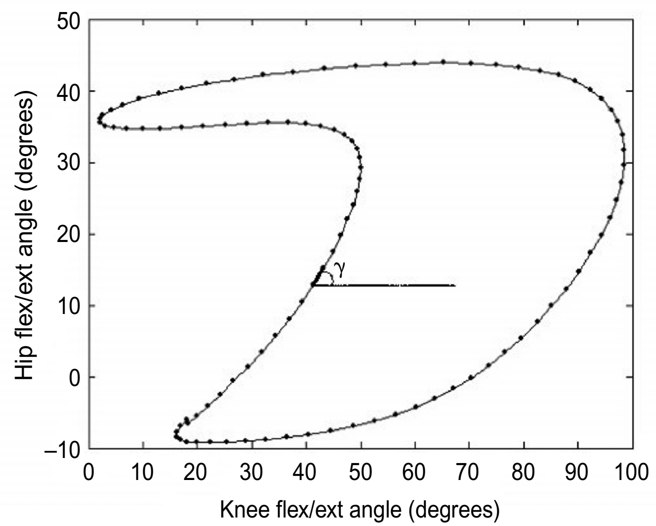

FIGURE 9.5 An illustration of the calculation for a coupling angle from an angle–angle plot.

The variability in the coupling angle over multiple cycles was then calculated at each frame-to-frame interval using circular statistics. However, no measurement was made of the magnitude of the frame-to-frame vectors, which may represent a limitation of this technique. This method of vector coding was also used by Heiderscheit et al. (2002) to compare variability in joint coordination during treadmill running in participants with and without patellofemoral pain.

The advantages of this technique, or collection of vector coding techniques, include no requirement for normalization (Hamill et al., 2000) which maintains the true spatial information in the data. This seems especially advantageous when using the technique of Tepavac and Field-Fote (2001), which incorporates a measurement of both the shape and magnitude of the angle–angle trajectories. Additionally, Field-Fote and Tepavac (2002) contended that vector coding techniques are more suitable than other methods such as relative phase analysis because “clinicians . . . are more likely to think of movement in terms of joint angles as opposed to phase values” (p. 710). The notion that vector coding is easier to relate to than relative phase seems reasonable. However, the output data from these techniques are not joint angles but the directions and magnitudes of frame-to-frame vectors, which may still be hard to understand conceptually.

A potential disadvantage of vector coding techniques is that they provide only spatial information, with no regard to temporal information (Hamill et al., 2000), which may limit the sensitivity to variability in coordination. Also, Heiderscheit et al. (2002) suggested that there is a potential problem with vector coding at times when joint motions change direction. Clark and Phillips (1993) hypothesized that these times of movement reversal are critical in the study of movement coordination, as are the apparent increases in variability in coordination (Ghez and Sainberg, 1995; Heiderscheit et al., 2002). However, as Heiderscheit et al. (2002) noted, during periods of movement reversal there is minimal joint displacement, and thus there is a cluster of data points on the relative motion diagram. The apparent increase in variability in coordination may simply be an artifact of the greater proximities of consecutive data points and the inherently greater sensitivity to slight changes in displacement.

Other Techniques

Techniques other than relative phase and vector coding have been used to quantify the coordination and variability in coordination between two body segments or joints. Two techniques that have received varying coverage in the literature are cross-correlations (Amblard et al., 1994) and normalized root mean squared differences (NoRMS: Sidaway et al., 1995).

Cross-correlations have been used to measure changes of coordination in an elite javelin thrower over 5 years (Morriss, 1998), assess changes in coordination during the learning of a task simulating skiing (Vereijken, van Emmerik, Whiting, and Newell, 1992; Whiting and Vereijken, 1993), monitor the acquisition of coordination during handwriting (Newell and van Emmerik, 1989), examine the effects of practice on coordination during dart throwing (McDonald, van Emmerik and Newell, 1989), and analyze the differences in intralimb coordination between expert and novice volleyball players performing a serve (Temprado, Della-Grast, Farrell and Laurent, 1997). Cross-correlations are based on the assumption that a linear relationship exists within segments or joints. However, it is not assumed that these segments or joints move in synchrony throughout the movement (Mullineaux, Bartlett and Bennett, 2001). By introducing time lags into the data—shifting data from one segment forward or backward in relation to the data of another segment by a given number of data points—it is possible to find high correlations in two segments between which there is a constant time lag (Mullineaux et al., 2001). Amblard et al. (1994) suggested that cross-correlations are particularly relevant for analyzing human movement, as there are often time lags between coordinated segments.

Cross-correlation appears to be similar to DRP, as the lag time from cross-correlation, if expressed relative to the oscillation period, indicates the phase relationship between the two segments (Temprado et al., 1997). However, determining whether the relationship is a phase lag or a phase lead can be problematic (Amblard et al., 1994). Advantages of cross-correlation include that no normalization procedure is required if the data are linear and, similar to DRP, no further manipulations are required other than what are normally carried out in the calculation of joint angles. However, if the data are nonlinear, a transformation procedure such as a log–log transformation is required to linearize the data (see Snedecor and Cochran, 1989). Nonetheless, if the coefficient of cross-correlation is still small after the transformation (there is still no linear relationship between the segments of interest), cross-correlations are unsuitable. Another disadvantage of the technique is that it provides only one measurement per movement cycle.

Sidaway et al. (1995) presented NoRMS, a technique for measuring the consistency or variability of several angle–angle trajectories. By measuring the resultant distance between the angle–angle coordinate of a curve and the angle–angle coordinate of the mean curve at each instant, a root mean square difference is calculated at each point in time. These values are averaged across the entire trial and subsequently normalized with respect to the number of cycles and the excursion of the mean plot using the equations presented by Sidaway et al. (1995) which were reduced by Mullineaux et al. (2001) into the following:

$$NoRMS = 100 * \left(\frac{\sum_{j=1}^{k} \sqrt{\sum_{i=1}^{n} \left(\bar{x}_A - x_{Ai}\right)^2 + \left(\bar{x}_B - x_{Bi}\right)^2} \Big/ n_j}{R} \right)$$

where A and B denote the two variables of interest, k is the number of cycles, n is the number of data points, R is the resultant excursion of the mean angle-angle curve over the entire cycle, $\bar{\chi}$ is the mean position of a given variable at the ith data point and χ is the position of a given variable at the ith data point on the jth cycle.

Sidaway et al. (1995) suggested that multiplication by 100 is used to make the resulting scores more manageable. However, the authors highlighted that, because linear statistical techniques are used on directional data, joint angles need to be greater than 0° and less than 360° and that the technique is not valid should joints, in an unusual situation, rotate through 360°. Sidaway et al. (1995) also suggested that it is more appropriate to express joint angles in relative terms to avoid neutral joint positions.

The NoRMS technique appears to offer a good measure of the variability in angle-angle traces that takes account of changes in the magnitude and shape of the plots. However, it gives no indication of the coordination between the segments of interest. Furthermore, there are some issues that need to be considered before using the NoRMS technique. Firstly, NoRMS in the form outlined by Sidaway et al. (1995) only provides one measure of coordination variability over the entire duration of the movement of interest. This might limit the use of the technique to analyse the variability in coordination during movements in which changes in the functional demands of the task over its duration may alter the magnitude of the variability during different phases - e.g., throughout the stance period of running (Heiderscheit et al., 2002). Moreover, the stage of the calculation during which the average cycle root mean square is divided by the resultant excursion of the mean angle-angle curve (see equation 9.4) appears to be similar to dividing the standard deviation by the mean value during the calculation of the coefficient of variation. Mullineaux (2000) stated that normalising data to the mean is appropriate if the means of the two sets of measurements are similar in size but it should not be done if the means are dissimilar as the results can be misleading. Therefore, in some instances where resultant excursions of the mean angle-angle curves are different between data sets under investigation, NoRMS may be inappropriate in the form presented by Sidaway et al. (1995). This technique has received little attention in the biomechanics and motor control literature.

Summary

There are advantages and disadvantages associated with all the techniques outlined in this chapter, but ultimately the chosen technique depends on the research question and the activity under scrutiny. Problems exist when applying relative phase techniques to nonsinusoidal data. However, when using vector coding techniques there are also issues surrounding the interpretation of variability in coordination during the reversal of the joint motion. Cross-correlations are unsuitable if the relationship between segments and joints is not linear. NoRMS might be misleading or indeed inappropriate for answering some research questions. Furthermore, Wheat et al. (2002) found that CRP and vector coding (Tepavac and Field-Fote, 2001) produced contradictory results for variability in coordination during certain times in the stance phase in running. These inconsistencies may result from the limitations discussed in this chapter, and further work is required to substantiate these preliminary findings. Finally, as Hamill et al. (2000) suggested, before choosing a particular technique, the researcher should be aware of the benefits and limitations of each and appreciate which are most suited to the movement or activity of interest.