Chapter 7
Use of the Uncontrolled Manifold (UCM) Approach to Understand Motor Variability, Motor Equivalence, and Self-motion

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7.1 Characterizing Variability in Motor Performance

Variability of motor output often has been considered a form of noise that interferes with reliable performance. This assumption, however, depends on the level of the motor system under consideration. For targeting tasks, variability of the end-effector position will affect the consistency of targeting, depending on the task requirements and the size of the target. Variability of coordination patterns used in artistic performance may impact the aesthetics of performance. However, variability at the level of the motor elements, including small variations in coordination patterns, often reflect task flexibility that is only possible when the motor system exhibits sufficient motor abundance (Latash 2012). Consider, for example, performing cardiopulmonary resuscitation (CPR) on an infant, with the index and middle fingers exerting the necessary force to produce adequate chest compression. If fluctuation in the compression force of one finger leads to a tendency for higher total force output, then reduction in the forces exerted by the other fingers is necessary to compensate and maintain a consistent total compression force. This is only possible because there are two fingers contributing to a single total force output. Note that an alternative approach would be to attempt to control precisely, to the extent possible, the variability of individual finger forces such that each finger generates approximately the same force on each repetition. The presence of compensatory finger forces, however, has been well documented (Latash et al. 2001, 2002a, 2002b), and is consistent with the notion of a functional synergy among the motor elements (Latash et al. 2007).

Determining whether variability of motor output reflects motor noise or flexible motor patterns is not trivial, however. Bernstein observed that when blacksmiths hit

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the chisel with the hammer there appeared to be more variability of the trajectories of individual joints than there was for the trajectory of the hammer (Bernstein 1967). This led him to conclude that a movement is never repeated in exactly the same manner. Although his intuition was correct, there was no way to clearly establish this fact. For one thing, the trajectory of the joints and the end effector (hammer) are measured in different units and the number of degrees of freedom of each is quite different. How does one compare variability of up to 10 joint motions (including scapular motion) measured in radians to the variability of three dimensions of end-effector motion measured in meters? Schöner and Scholz (Schöner 1995; Scholz and Schoner 1999) developed the uncontrolled manifold (UCM) approach to overcome this problem and to quantify statistically the extent to which variability of motor elements tends to lead to noise or error in performance versus reflecting the use of flexible patterns of coordination. In this approach, all analysis to answer this question is performed at the level of the motor components, e.g., joint motions, finger forces, and muscle modes.

To accomplish this, the UCM approach requires a model that relates how changes in elemental variables affect the task level (e.g., hand position in space, total force output). This model can be obtained formally, as when relating joint motions to movement of the hand in space (e.g., $\Delta x = l_1 \cos\theta_1 + \cos(\theta_1 + \theta_2) + \cdots$) or via regression analysis when a formal model is not readily available or excessively complicated (Freitas and Scholz 2010). The null space of the equation relating the task space to the space of motor elements provides a linear estimate of all combinations of the motor elements that do not affect the value of the task variable at that point in a movement trajectory or in time (e.g., $J(\theta_{\text{mean}})\,\Delta\theta_i = 0$ where J is the Jacobian matrix of partial derivatives relating small changes in the elemental variables to changes in the task variable). The null space is computed around the mean value of the motor elements (θ_{mean}) at each point in the movement trajectory. Experimentally measured mean-free values of the motor elements ($\Delta\theta_i = \theta_i - \theta_{\text{mean}}$) for each movement repetition at a given point in the normalized movement are projected into the null space and its compliment, or range space (the subspace of motor elements in which different combinations of the motor elements lead to different values of the task variable of interest). This is done for each repetition and the variance of the projection lengths is then computed and normalized to the dimensions of the subspace to make the analysis more conservative. Greater variance in the null space or UCM subspace than in the range space suggests a control strategy in which the central nervous system provides stabilizing control signals that restrict variations of the motor elements when they affect the desired value of the task variable but allows for some degree of variability in combinations of those variables if they have no effect on the task variable (i.e., variations within the UCM).

Studies of many different motor tasks have shown that variability at the level of motor elements is more consistent with the use of flexible combinations of those elements that preserve a stable state (e.g., posture) or produce a consistent trajectory (e.g., reaching) of a task-level variable (e.g., center of mass position, trajectory of the hand). In contrast, range space variability typically is shown to be significantly smaller (Scholz and Schoner 1999; Scholz et al. 2000; Latash et al. 2001; Scholz et al. 2001, 2002; Krishnamoorthy et al. 2003, 2007; Latash et al. 2002a). UCM analysis also has been able to differentiate between movement synergies in persons with neurological dysfunction and healthy control subjects (Reisman and Scholz 2006; Park et al. 2012, 2013). In addition, different hypothesized task variables can be evaluated with this approach to help determine what variables are of greatest importance to task performance (Scholz et al. 2000). The results are in agreement with the minimum intervention principle, which suggests that allowing variability in redundant (abundant) dimensions is the optimal control strategy in the face of uncertainty (Todorov and Jordan 2003), although a control structure more in line with the UCM hypothesis than optimal control has been shown to better account for detailed characteristics of movement trajectories (Martin et al. 2009).

The dependence of the outcome of a UCM analysis of motor variability on the variables used to describe the effector system has recently been criticized (Sternad et al. 2010). For example, the authors suggest that movements may equally well be planned in joint or segment angle coordinates. They provide an example of a minimally redundant effector system in which the UCM method leads to quite different results when either of these sets of variables is used. This criticism is relevant and emphasizes that researchers must make considered choices of the variables used for analysis. Three clarifications are in order, however:

1. A choice of variables fixes the space in which configurations of the effector are described. If we choose joint angles as variables, then we describe the effector in joint space. A point in that space represents one particular configuration of the effector. A metric must be fixed as well, which assesses the distance between any two points in that space, that is, between two configurations of the effector. Typically, the Euclidian metric is used, in which the squared distances along each of a set of orthogonal coordinate axes are summed and the square root is taken. The UCM approach is then actually invariant under any change of coordinate frame that leaves the metric invariant (Schöner and Scholz 2007). This includes, in particular, rotations of the coordinate frame. This invariance reflects the fact that the UCM analysis is based on a geometrical view of variance, in which the shape of the cloud of points in joint space is observed across trials at a particular point during a movement. If that shape is elongated along the direction of the null space, then the UCM hypothesis is confirmed. The shape of the cloud of points is invariant under any coordinate transform that preserves the metric of the space spanned by the chosen variables. This is useful in some cases, such as for the shoulder joint, for which there is no principled way to select a particular coordinate frame to represent the three degrees of freedom that reside in that joint. Any orthogonal set of coordinate axis is equally meaningful, so that invariance under rotation of a coordinate frame is desirable. The randomization method (Müller and Sternad 2004), in contrast, is essentially a form of nonlinear, multivariate correlation. In that approach, the coordinate frames matter as they do for correlation. If the cloud of points is elongated along a coordinate axis, for instance, then that shape is not picked up as correlation but as inherent variability of that particular degree of freedom.

2. Transformations that do not leave the metric invariant matter in the analysis of variance and this is how the choices of variables that set up the configuration space come into play. For instance, representing joint configurations through segment angles or through joint angles does not lead to the same shape of the cloud of points. Mathematically, going from segment angles to joint angles is a transformation that does not leave distances invariant: It is not a metric preserving transformation, unlike the rigid rotations that may be used to link different orthogonal axes for joint angles anchored in the shoulder. This dependence on the embedding space is shared, of course, by all approaches to the analysis of multidimensional variance (e.g., Müller and Sternad 2004; Cusumano and Cesari 2006).
3. Fortunately, the choice of embedding space can be guided by what we know about physiology. Specifically, the choice of joint over segment angles is not arbitrary. Known sensory receptors provide information to the nervous system about changes in joint angles (Grigg 1994). There are no known sensory receptors signaling orientation of a limb segment in external space, although transformation of sensory receptor information can be used to estimate limb orientation (Poppele et al. 2001). Segment angles are inherently dependent on each other. For example, a flexion of the ankle brought about by a signal sent to muscles that act on the ankle joint leads to changes of all segment angles along the kinematic chain of the upright body, including joints not linked to the ankle by any muscle. Similarly, changing the segment angle that the humerus forms with an external reference frame also changes the segment angles of the forearm and hand, without any activity by muscles acting on these more distal joints. Thus, distal segment motion in an open kinematic chain is not independent of proximal segment motion. This is not the case with joint angles. Changing one joint angle does not necessarily affect another joint angle, unless there are particular mechanisms that bring about such dependence like multi-articular muscles or coordinated neural signals.

Thus, it seems to us that the best of two worlds is achieved by combining the geometrical view of the UCM approach, which is conceptually attractive, with the analytical power of the correlational approach. This is now routinely done by researchers who select a set of variables and a particular coordinate frame based on substantive hypotheses. They can then use the surrogate data procedure of the correlational approach to verify if the shape of the variance in the UCM analysis truly comes from covariation among the variables identified as meaningful rather than from inherent differences in variance among the different degrees of freedom (see, for example, Yen and Chang 2009; Verrel et al. 2010).

7.2 Quantifying Motor Equivalence

More recently, the geometrical perspective of the UCM approach has been used to address additional issues in motor control, namely, motor equivalence and self-motion. The term motor equivalence has been used in a variety of ways, but is defined

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here as a change in the configuration of motor elements after a perturbation that tends to preserve the outcome of a task or the stability of a task-relevant variable. Kelso and colleagues (Kelso et al. 1984) performed a seminal study of motor equivalence in the context of the control of speech utterances. They found that adjustments in the articulators were task-specific, dependent on the nonsense syllable that subjects spoke when a perturbation was delivered to depress the jaw. Further evidence was provided when naïve subjects were unable to distinguish utterances performed during perturbed and nonperturbed trials. However, in many cases, distinguishing between adjustments of motor coordination that lead to disturbance of the task versus being a reflection of motor equivalent adjustments to preserve the task is not trivial. For example, when reaching to a target, a transient perturbation of a joint will lead to at least some effect on the motion of the end effector. If the end effector still reaches the target, this suggests that motor equivalence must be present. What if the hand, however, hits the target but deviates from its position on nonperturbed trials or what effect does the perturbation have on the path of the hand itself? Presuming that there are readjustments in the joint configuration or muscle firing patterns due to the perturbation, how can one determine the extent to which the adjustments account for observed deviations in the hand path or whether more of the adjustments tend to act to preserve the hand path? A modification of the UCM approach allows this question to be addressed quantitatively. If one takes a set of nonperturbed trials, the null space of the Jacobian matrix relating small changes in the motor elements to changes in a hypothesized task variable (e.g., the hand position) can be computed using the mean value of the motor elements across trials. This null space corresponds, as in UCM variance analysis, to a linear estimation of all combinations of joint configurations that lead to the same value of the task variable. Again, this analysis is performed at each point in the normalized (to 100 %) movement.

One can then obtain the vector of the configuration of motor elements from a perturbed (pert) trial, subtract it from the mean of the nonperturbed (nonpert) trials $\left(\theta_{\text{pert}} - \bar{\theta}_{\text{non-pert}}\right)$, and project this difference vector into the null space (UCM) and range space of the nonperturbed trials. If the null space projection is significantly larger than the range space projection, then this suggests that more of the adjustment in the joint configuration due to the perturbation is motor equivalent, tending to preserve the nonperturbed value of the relevant task variable. This approach, therefore, provides a statistical method for determining the extent to which motor equivalence is present.

In a collaborative study with Fay Horak and John Jeka, motor equivalence relative to the position of the center of mass of the body was measured in persons standing on a moveable force platform that was perturbed by different amplitudes, keeping the velocity of perturbation constant (Scholz et al. 2007). An example of the results obtained immediately after the transient perturbation are presented in Fig. 7.1. Note that the projection into the UCM subspace or null space was larger, and significantly so, than the projection into the range space, both computed based on the nonperturbed trials. This difference increased with greater amplitudes of perturbation. Thus, most of the change in the joint configuration as a result of the perturbation was motor equivalent, tending to preserve the pre-perturbation position of the center of mass of the body.

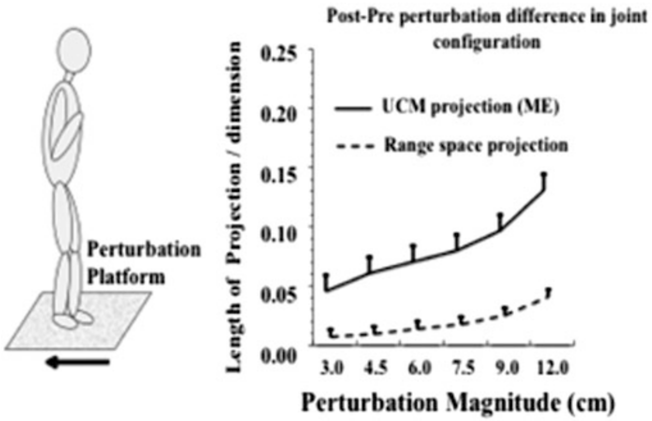

Fig. 7.1 *Left:* Participants stood upright when the support platform was abruptly moved by a varied amount (perturbation amplitude). *Right:* Six degrees of freedom were included in a motor equivalence analysis. The difference vector between joint configurations in perturbed trials from the mean configuration in unperturbed trials was projected into the UCM subspace (*solid line*) and the range spaced (*dashed line*). The plot shows the average length of these differences vectors across perturbation trials per degree of freedom together with the SME (*error bars*) as functions of the perturbation amplitude. The data are from Scholz et al. 2007 (Fig. 4 there)

7.2.1 Quantifying Self-Motion

UCM variance analysis indicates how fluctuations of the motor elements across repetitions or, in the case of relatively steady state behavior, across time are structured. For example, in upright posture, to what extent do joint fluctuations over time lead to postural sway of the center of mass versus being coordinated to flexibly stabilize the center of mass location? Nonetheless, fluctuations of the motor elements could be relatively small or large, depending on the task. The amount of self-motion provides an estimate of the magnitude of changes in the motor elements that lie in the UCM subspace and, therefore, do not affect the value of a task variable and those that change the value of the task variable. The concept of self-motion comes from the robotics of redundant effectors and, in that context, refers to the magnitude of the vector of time-dependent changes (e.g., velocity) in the motor elements that lies in the null space or UCM subspace. In contrast, range space motion refers to that component of this vector that lies in the range space, or actually moves the task variable with reference to which the analysis is applied.

Consider reaching to a target with the hand. One might suspect that the most efficient movement of the hand would occur if the joints were coordinated such that their velocities were directed primarily toward that goal. If so, then the range space velocity component of the joints, which actually moves the hand in space, would be expected to be substantially larger than the self-motion or UCM component. Self-motion might be advantageous in some circumstances, however. For example, when carrying a relatively full glass of Guinness stout, if a fly lands on your elbow, you

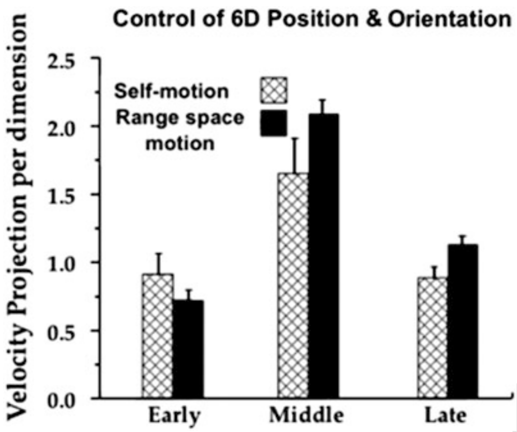

Fig. 7.2 Reaching with ten degrees of freedom to a target was analyzed with respect to self-motion, using a Jacobian that took into account both the 3D end-effector position and the 3D orientation of the hand for a total of six degrees of freedom in task space. Mean self-motion and range space motion per degree of freedom averaged across participants is shown for the early, middle, and late phase of reaching when reaching at a fast speed to a target. Data are from Scholz et al. (2011; compare to Fig. 3 there, which includes other conditions as well)

might want to flick the elbow to get it to go away without spilling the precious stout! Internal motion of the arm joints that does not affect the hand position is, by definition, self-motion. But how much self-motion is present for a given task when motion to achieve a secondary task is not required?

To answer this question, we developed a method of analysis that can be carried out on individual trials or on means across trials. The method was adapted from the UCM approach to the analysis of variance. The Jacobian, J, that relates the joint velocity vector, $\dot{\theta}$, to the velocity of the hand, $\dot{x} = J(\theta)\dot{\theta}$, is computed from a geometrical model of the effector. It is evaluated at the instantaneous joint configuration, θ, at each point in time. Based on this Jacobian, the null (UCM) and range spaces can be determined. The joint velocity vector, $\dot{\theta}$, is computed from the time series by numerical differentiation and is projected into either subspace. Finally, the length of these projections is computed and divided by the number of dimensions of each subspace.

Figure 7.2 presents an example of this analysis from a recent article investigating self-motion at different speeds of reaching (Scholz et al. 2011). The results for reaching at a self-selected fast speed are depicted. Note that although range space motion (component of the joint velocity vector projection that moves the hand in space) generally was larger than self-motion, self-motion was nonetheless quite substantial. The results were similar at slow and moderate speeds of reaching, although self-motion was not quite as large as compared to range space motion. Of interest was that at all speeds of reaching, self-motion actually was larger than range space motion at the early stage of reaching, probably because the arm had to be adjusted to exit the trough in which it rested as the reach was initiated.

The results suggest that even during the performance of goal-oriented targeting tasks there is a substantial amount of self-motion, i.e., joint configuration motion within the UCM subspace of joint space, even when an obvious secondary task is not involved. It is hypothesized that this amount of self-motion is a reflection of the nature of the control system that minimally restricts combinations of motor elements for a task that do not interfere with successful performance even when the configurations deviate from the initially planned configuration.

7.3 Conclusion

The UCM approach was developed originally to investigate the role of motor variance and has been successfully applied to a variety of motor tasks from finger force production to reaching to postural control. In most cases, variance consistent with flexible combinations of the motor elements that maintain a consistent value of an important task variable has been shown to be significantly greater than variance leading to variability of the task variable. The approach allows one to test hypotheses about the importance of different task-relevant variables based on the structure of variance of the underlying motor elements and to evaluate how different motor elements contribute to that structure.

Recently, the approach has been extended to address additional important issues in motor control such as motor equivalence in the presence of a perturbation and the extent to which motor abundance is used in the control of motor tasks through self-motion analysis. A model of a control strategy based on the UCM hypothesis and consistent with the recent results was developed by Martin, Scholz, and Schöner (Martin et al. 2009) and applied to postural control by Reimann et al. (2011). We believe that the geometrical perspective offered by UCM thinking will be useful both to interpret experimental signatures of control hypotheses and to investigate possible neural processes that bring about the coordination of the many degrees of freedom of the motor system. Ultimately, we will need to understand how spatial information and timing constraints for the motion of effectors in space can be translated to control signals at the level of each muscle (Bullock et al. 1993; Butz et al. 2007). That transformation sets up the geometry uncovered by the UCM method.

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