31

Measurement and Analysis of Sensory-Motor Performance: Tracking Tasks

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31.1 Introduction

The human nervous system is capable of simultaneous, integrated, and coordinated control of 100–150 mechanical degrees of freedom of movement in the body via tensions generated by about 700 muscles. In its widest context, movement is carried out by a *sensory-motor system* (= sensorimotor system) comprising multiple sensors (visual, auditory, proprioceptive), multiple actuators (muscles and skeletal system), and an intermediary processor which can be summarized as a multiple-input multiple-output nonlinear dynamic adaptive control system. This grand control system comprises a large number of interconnected processors and sub-controllers at various sites in the central nervous system (CNS) of which the more important are the cerebral cortex, thalamus, basal ganglia, cerebellum, and spinal cord. It is capable of responding with remarkable accuracy, speed (when necessary), appropriateness, versatility, and adaptability to a wide spectrum of continuous and discrete stimuli and conditions. It also possesses considerable capabilities for learning new skills, for long-term improvement of performance with practice, and being able to switch quickly between quite different tasks. Certainly, by contrast, it is orders of magnitude more complex and sophisticated than the most advanced robotic systems currently available—although the latter can have superior and often highly desirable attributes such as precision and repeatability and a much greater immunity from factors such as fatigue, distraction, boredom, and lack of motivation!

This chapter has a primary focus on the sensory-motor control function. First, it introduces several important concepts relating to *sensory-motor control, accuracy of movement, a performance resource*, and *a performance capacity.* Second, it provides an overview of apparatuses and methods for the *measurement* and *analysis* of complex sensory-motor performance of the *upper-limbs* (cf. lower-limbs and oculomotor system) by means of *tracking tasks.*

31.2 Basic Principles

31.2.1 Sensory-Motor Control and Accuracy of Movement

The sensory-motor control system is a central component of the sensory-motor system and, from the perspective of Kondraske's *elemental resource model* of human performance (1995, 2006a), can be considered as a hierarchy of multiple interconnected sensory-motor controllers in the *central processing and skills domains* (cf. environmental interface domain, comprising sensors and actuators, and life-sustaining domains) of the elemental resource model. These controllers range from low-level elemental level controllers for control of movement around single joints, through intermediate-level controllers needed to generate integrated movements of an entire limb and involving multiple joints and degrees of freedom, and high-level controllers and processors to enable coordinated synergistic multi-limb movements and the carrying out of *central executive* functions concerned with allocation and switching of resources for execution of multiple tasks simultaneously.

Each of these controllers is considered to possess limited *performance resources*—or *performance capacities*—necessary to carry out their control functions. Performance resources are characterized by dimensions of performance, which for controllers are *accuracy of movement* (including steadiness and stability) and *speed of movement*. Accuracy is the most important of these and can be divided into four major classes:

1. Spatial accuracy—Required by tasks which are *self-paced* and for which time taken is of secondary or minimal importance and includes tracing (e.g., map-tracking), walking, reaching, grasping, and, in fact, many activities of daily living. Limitation in speed performance resources should have no influence on this class of accuracy.
2. Spatial accuracy with time constraints—Identical to "spatial accuracy" except that, in addition to accuracy, speed of execution of task is also of importance. Because maximal performance capacities for accuracy and speed of movement cannot, in general, be realized simultaneously, the carrying out of such tasks must necessarily involve speed-accuracy trade-offs (Fitts, 1954; Fitts and Posner, 1967; Murata and Iwase, 2001; Battaglia and Schrater, 2007; Jax et al., 2007; Bye and Neilson, 2008). The extent to which accuracy is sacrificed for increased speed of execution, or vice versa, is dependent on the actual or perceived relative importance of accuracy and speed.

3. Temporal accuracy—Required by tasks which place minimal demands on positional accuracy and includes single and multi-finger tapping and foot tapping.
4. Spatiotemporal accuracy—Required by tasks which place considerable demand on attainment of simultaneous spatial and temporal accuracy. This includes externally paced positional tasks such as tracking, driving a vehicle, flying a plane, ball games and sports, and video games. It should be stressed, however, that most self-paced tasks also involve a considerable interrelationship between space and time.

Tracking tasks are well established as able to provide one of the most accurate and flexible means for laboratory-based measurement of spatiotemporal accuracy and, thus, of the *performance capacity* of sensory-motor control or sensory-motor coordination. In addition, they provide an unsurpassed framework for studies of the underlying control mechanisms of motor function (Lynn et al., 1979; Cooper et al., 1989; Neilson et al., 1993, 1998; Davidson et al., 2000, 2002; Neilson and Neilson, 2002)—the potential for which was recognized as early as 1943 as seen in writings by Craik (1966). They have achieved this status through their (a) ability to maximally stress the accuracy *dimension of performance* and, hence, the corresponding control performance resource, (b) continuous nature and wide range of type and characteristics of input target signals they permit, (c) facility for a wide range of 1-D, 2-D, and 2-D sensors for measuring a subject's motor output, and (d) measure of continuous performance (cf. discrete tasks such as reaction time tests).

From this perspective, it will be of little surprise to find that tracking tasks are the primary thrust of this chapter.

31.2.2 Influence of Lower-Level Performance Resources on Higher-Level Control Performance Resources

By their very nature, tasks which enable one to measure spatiotemporal accuracy are complex or higher-level sensory-motor tasks. These place demands on a large number of lower-level performance resources such as visual acuity, visual perception, range of movement, strength, simple reaction times, acceleration/deceleration, static steadiness, dynamic steadiness, prediction, memory, open-loop movements, concentration span, central executive function (attention switching, divided attention, multitasking), utilization of preview, and learning.

It is, therefore, important to ask: If there are so many performance resources involved in tracking, can tracking performance provide an accurate estimate of sensory-motor control performance capacities? Or, if differences are seen in tracking performance between subjects, do these necessarily indicate comparable differences in control performance capacities? Yes, they can, but only if the control resource is the *only* resource being maximally stressed during the tracking task. Confirmation that the other performance resources are not also being maximally stressed for a particular subject can be ascertained by two means. First, by independently measuring the capacity of the other performance resources and confirming that these are considerably greater than that determined as necessary for the tracking task in question. For example, if the speed range for a certain reference group on a nontarget speed test is 650–1250 mm/s and the highest speed of a tracking target signal is 240 mm/s, then one can be reasonably confident that intra-group differences in performance on the tracking task are unrelated to intra-group differences in speed. Second, where this process is less straightforward or not possible, it may be possible to alter the demands imposed by the task on the performance resource in question. For example, one could see whether visual acuity was being maximally stressed in a tracking task (and, hence, be a significant limiting factor to the performance obtained) by increasing or decreasing the eye-screen distance. Similarly, one could look at strength in this context by altering the friction, damping, or inertia of the sensor, or at range of movement by altering the gain of the sensor.

The conclusion that a task and a performance resource are unrelated for a particular group does not, of course, mean that this can necessarily be extrapolated to some other group. For example, strength may be uncorrelated with tracking performance in healthy males yet be a factor responsible for poorer tracking performance in females (Jones et al., 1986) and the primary factor in the paretic arm of subjects who have suffered a stroke (Jones et al., 1989).

The foregoing discussion is based on the concept of an assumption that if a task requires less than the absolute maximum available of a particular performance resource, then performance on that task will be independent of that performance resource. Not surprisingly, the reality is unlikely to be this simplistic or clear-cut! If, for example, a tracking task places moderate sub-maximal demands on several performance resources, these performance resources will be stressed to varying levels such that the subject may tend to optimize the utilization of those resources (Kondraske, 1995, 2006a) so as to achieve an acceptable balance between accuracy, speed, stress/effort, and fatigue (physical and cognitive). Thus, although strength available maybe much greater than strength needed (i.e., Resource available >> Resource demand) for both male and female individuals, the differential in strength could well be responsible for male individuals performing better on tracking tasks than female individuals due to the higher acceleration performance resource in male individuals and, hence, ability to correct tracking errors faster (Jones et al., 1986).

31.3 Measurement of Sensory-Motor Performance

31.3.1 Techniques: An Overview

Tracking tasks are the primary methodological approach outlined in this chapter for measurement of sensory-motor control performance. There are, however, a large number of other approaches, each with their own set of apparatuses and methods, which can provide similar or different data on aspects of sensory-motor control performance. It is possible to give only a cursory mention of these other techniques in this chapter.

Hand and foot test boards comprising multiple touch-plate sensors provide measures of accuracy and speed of lateral reaching-tapping abilities (Kondraske et al., 1984, 1988).

Measurement of steadiness and tremor in an upper-limb, lower-limb, or segment of either, particularly when subtended, can be made using variable-size holes, accelerometers, or force transducers (Potvin et al., 1975). A dual-axis capacitive transducer developed by Kondraske et al. (1984) provides an improved means of quantifying steadiness and tremor due to it requiring no mechanical connection to the subject (i.e., no added inertia) and by providing an output of limb position as opposed to less informative measures of acceleration or force. Interestingly, tests of steadiness can be appropriately considered as a category of tracking tasks in which the target is static. The same is also true for measurement of postural stability using force balance platforms, whether for standing (Kondraske et al., 1984; Myklebust et al., 2009) or sitting (Riedel et al., 1992; Schilling et al., 2009).

While the primary focus in this chapter is on measuring tracking performance in the upper limbs, many of the tasks can equally be applied to measurement of oculomotor function, including random targets for assessing smooth pursuit function and predictable and unpredictable step targets for assessing saccadic function (MacAskill et al., 2002; Muir et al., 2003; Heitger et al., 2004, 2008, 2009).

31.3.2 Tracking Tasks: An Overview

A tracking task is a laboratory-based test apparatus characterized by a continuous input signal—the target—which a subject must attempt to match as closely as possible by his/her output response by controlling the position of (or force applied to) some sensor. It provides unequalled opportunities for wide-ranging experimental control over sensors, displays, target signals, dimensionality (degrees of freedom), control modes, controlled system dynamics, and sensor-display compatibility, as well as the application of a vast armamentarium of linear and nonlinear techniques for response signal analysis and systems identification. Because of this, the tracking task has proven to be *the* most powerful and versatile tool for assessing, studying, and modeling higher-level functioning of the human "black-box" sensory-motor system.

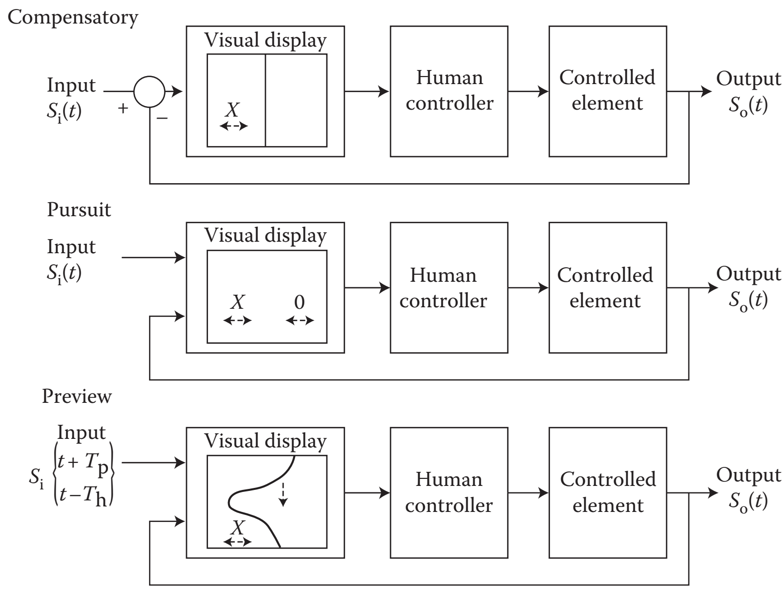

FIGURE 31.1 Modes of tracking. (i) Compensatory: subject aims to keep his error signal ***X*** (= input signal – output signal = $s_i(t) - s_o(t)$) on the stationary vertical line; (ii) pursuit: subject aims to keep his output signal ***X***, $s_o(t)$, on the target input signal ***O***, $s_i(t)$; (iii) preview: subject aims to keep his output signal ***X***, $s_o(t)$, on the descending target input signal $[s_i(t + T_p)$ to $s_i(t - T_h)]$, where t = present time, T_p = preview time, T_h = history or postview time.

There are three basic categories of tracking tasks, differing primarily in their visual display and corresponding control system (Figure 31.1). The pursuit task displays both the present input and output signals, whereas the compensatory task displays only the difference or error signal between these. The preview task (Poulton, 1964; Welford, 1968; Jones and Donaldson, 1986; Jones et al., 1996; Klaver et al., 2004) (Figure 31.2) is similar to the pursuit task except that the subject can see in advance where the input signal is going to be and plan accordingly to minimize the resultant error signal. Tracing tasks (Driscoll, 1975; Stern et al., 1983; Hocherman and Aharon-Peretz, 1994; Gowen and Miall, 2006) are effectively self-paced 2-D preview tracking tasks.The input–output nature of tracking tasks has made them most suitable for analysis using engineering control theories. This has led to

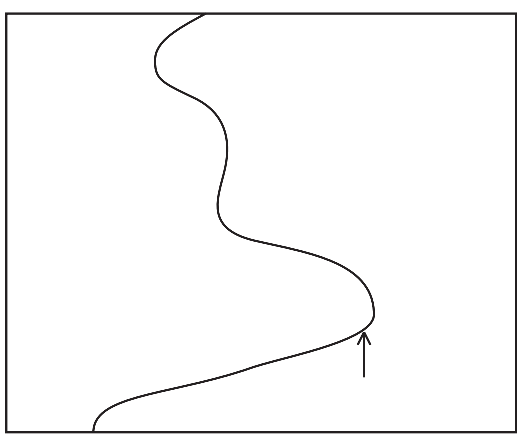

FIGURE 31.2 Visual display for random tracking with a preview of 8.0 s and postview of 1.1 s.

the common view of pursuit tracking as a task involving continuous negative feedback (Notterman et al., 1982) but there is evidence that tracking viewed as a series of discrete events is more appropriate (Bösser, 1984; Neilson et al., 1988a; Bye and Neilson, 2010). The inclusion of preview of the input signal greatly complicates characterization of the human controller and Sheridan (1966) suggested three models of preview control which employ the notions of constrained preview and nonuniform importance of input. Lynn et al. (1979) and Neilson et al. (1992) have also demonstrated how, by treating the neurologically impaired subject as a black-box, control analysis can lead to further information on underlying neurological control mechanisms. Davidson et al. (2000, 2002) and Ghous and Neilson (2002) have done likewise in their investigations of open-loop control mechanisms in healthy subjects.

Despite the widespread utilization and acceptance of tracking tasks as a powerful and versatile means for quantifying and studying sensory-motor control performance and capacities, there is little available on the market in this area. The most obvious exception to this is the photoelectric pursuit rotor which is ubiquitous in the motor behavior laboratories of university psychology departments and has been available since the 1950s (Welford, 1968; Schmidt, 1982; Siegel, 1985). It is a paced 2-D task with a target with the periodic on each revolution. Although inexpensive, the pursuit rotor is a crude tracking task allowing limited control over target signals and possessing a very gross performance analysis in terms of time on target. Thus, essentially all of the many and varied tracking tasks which have been used in countless experimental studies around the world, with some of these tasks having moved into clinical neurology and rehabilitation environments as objective and quantitative assessment tools, have been developed by the users themselves for their specific objectives. That is, surprisingly, there are essentially no computer-based tracking test systems commercially available. The need for such, including sensors for both upper- and lower limbs, seems obvious as this would open up the possibility of a much broader and widespread use of tracking tasks. In particular, this would help facilitate much greater utilization of tracking tasks outside of traditional research areas and in more routine assessment applications in clinical, rehabilitative, vocational, sports, and other environments.

Whatever the reason(s) for needing a tracking task to quantify sensory-motor control performance or capacity, there are a number of options available and factors to be considered in choosing or designing a tracking task. These are discussed in Sections 31.3.3 through 31.3.14.

31.3.3 Sensors

Sensors for measuring a subject's motor output in 1-D tracking tasks can be categorized under (a) movements involving a single degree of freedom such as flexion–extension rotation around a single joint such as elbow (Lynn et al., 1977; Deuschl et al., 1996; O'Dwyer et al., 1996; Soliveri et al., 1997), wrist (Warabi et al., 1986; Gibson et al., 1987; Johnson et al., 1996; Liu et al., 1999; Feys et al., 2005; Notley et al., 2007), or a finger, or pronation–supination of the wrist (Evarts et al., 1981), and (b) movements involving two or more degrees of freedom of a body part (e.g., hand)—that is, coordinated movement at multiple joints—which are either 1-D, such as some form of linear transducer (Patrick and Mutlusoy, 1982; Baroni et al., 1984; van den Berg et al., 1987; Johnson et al., 1996) or 2-D, such as steering wheel (Buck, 1982; Ferslew et al., 1982; Jones and Donaldson, 1986; Jones et al., 1993, 2002; Davidson et al., 2000, 2002; Heitger et al., 2004, 2007; Peiris et al., 2006, 2011; Innes et al., 2007, 2009a; Hoggarth et al., 2010), stirring wheel (De Souza et al., 1980), position stick (i.e., 1-D joystick) (Potvin et al., 1977; Neilson and Neilson, 1980; Miall et al., 1985; O'Dwyer and Neilson, 1998; Watson and Jones, 1998), joystick (Kondraske et al., 1984; Anderson, 1986; Behbehani et al., 1988; Dalrymple-Alford et al., 1994; Watson et al., 1997; Watson and Jones, 1998; Gonzalez et al., 2000; Allen et al., 2007; Poudel et al., 2008, 2010b; Siengsukon and Boyd, 2009a), finger-controlled rotating knob (Neilson et al., 1993), light-pen (Neilson and Neilson, 1980), and MRI-compatible pneumatic squeeze bulb/ball (Oishi et al., 2011) (e.g., Current Designs—www.curdes.

com). Force sticks, utilizing strain-gauge transducers mounted on a cantilever, are also commonly used as sensors (Garvey, 1960; Potvin et al., 1977; Miller and Freund, 1980; Kondraske et al., 1984; Anderson, 1986; van den Berg et al., 1987; Barr et al., 1988; Stelmach and Worrington, 1988; Chelette et al., 1995; Van Orden et al., 2000; Allen et al., 2007; Jasper et al., 2010). Isometric integrated EMG (i.e., full-wave rectification and low-pass filtering of the raw EMG) can also be used to control the tracking response cursor, as was done by Neilson et al. (1990) to help show that impairment of sensory-motor learning is the primary cause of functional disability in cerebral palsy.

Sensors for 2-D tasks must, of course, be capable of moving with and recording two degrees of freedom. Joysticks are commonly used for this and range in size from small, for wrist/finger movement (Bloxham et al., 1984; Anderson, 1986; Frith et al., 1986; Neilson et al., 1998; Gonzalez et al., 2000; Allen et al., 2007), including MRI-compatible joysticks (Poudel, 2008, 2010b) (e.g., Current Designs—www.curdes.com), up to large floor-mounted joysticks for arm movements primarily involving shoulder and elbow function (Kondraske et al., 1984; Anderson, 1986; Behbehani et al., 1988; Jones et al., 1993; Dalrymple-Alford et al., 1994; Watson et al., 1997; Watson and Jones, 1998). Other 2-D task sensors include computer mouse (Korteling and Kaptein, 1996), computer track-ball (Petrilli et al., 2005), hand-held stylus for the photoelectric pursuit rotor (Schmidt, 1982; Siegel, 1985), plexiglass tracing (Driscoll, 1975; Stern et al., 1983; Hocherman and Aharon-Peretz, 1994; Gowen and Miall, 2006), touch-sensitive screen (Engel and Soechting, 2000), and tasks utilizing sonic digitizers (Stern, 1986; Viviani and Mounoud, 1990; Hocherman and Aharon-Peretz, 1994). Abend et al. (1982) and Flash and Hogan (1985) used a two-joint mechanical arm to restrict hand movements to the horizontal plane in the investigation of CNS control of two-joint (shoulder and elbow) movements in trajectory formation. Stern et al. (1983) simply used the subject's finger as the sensor for a tracing task on a vertical plexiglass screen; a video camera behind the screen recorded finger movements. Novel whole-body 2-D tracking is also possible by having subjects alter their posture while standing on a dual-axis force platform (Kondraske et al., 1984).

1-D sensors can also be used in 2-D tasks by way of bimanual tracking. For example, O'Dwyer and Neilson (1995) and Neilson and Neilson (2002) used two 1-D joysticks to investigate dynamic synergies between the right and left arms.

More recently, high spatial precision 3-D sensors have become available via infrared LED markers combined and camera system (e.g., Optotrak—www.ndigital.com/lifesciences/certus-motioncapture-system.php) or electromagnetic trackers (e.g., Polhemus—polhemus.com; Flock-of-Birds, trakSTAR—www.ascension-tech.com) and play an important role in 3-D virtual-environment systems (Mrotek et al., 2006; Myall et al., 2008).

31.3.4 Displays

In the early days of tracking, mechanical-based displays were used, such as a rotating smoked drum (Vince, 1948), the ubiquitous pursuit rotor, and a paper-strip preview task (Poulton, 1964; Welford, 1968). An oscilloscope was used in a large number of tracking tasks, initially driven by analog circuitry (Flowers, 1976; Anderson, 1986; Sheridan et al., 1987) but later by D/A outputs on digital computers (Kondraske et al., 1984; Miall et al., 1985; Sheridan et al., 1987; Cooper et al., 1989). Standard raster-based television screens have been used by some workers (Potvin et al., 1977; Beppu et al., 1984). Nonraster vector graphics displays, such as Digital Equipment's VT11 dynamic graphics unit, proved valuable during the PDP-era as a means for generating more complex dynamic stimuli such as squares (Neilson and Neilson, 1980; Frith et al., 1986) and preview (Jones and Donaldson, 1986) (Figure 31.2). More recently, raster-based color graphics boards have allowed impressive static displays and simple dynamic tracking displays to be generated on PCs. However, such boards are not, in general, immediately amenable for the generation of flawless dynamic displays involving more complex stimuli, such as required for preview tracking. Jones et al. (1993) overcame this drawback by the use of specially written high-speed assembly-language routines for driving their display. These generated a display of the target and the subject's response marker by considering the video memory (configured in EGA mode) as four overlapping planes, each switchable (via a mask), and each capable of displaying the background color and a single color from a palette. Two planes were used to display the target, with the remaining two being used to display the subject's pointer. The current target was displayed on one target plane, while the next view of the target, in its new position, was being drawn on the other nondisplayed target plane. The role of the two planes was reversed when the computer received a vertical synchronization interrupt from the graphics controller indicating the completion of a raster. Through a combination of a high update-rate of 60.34 Hz (i.e., the vertical interrupt frequency), assembly language, and dual display buffers, it was possible to obtain an extremely smooth dynamic color display. Their system for tracking and other quantitative sensory-motor assessments was further enhanced through its facility to generate dynamic color graphics on two high-resolution monitors simultaneously: one for the tracking display, and one for use by the assessor for task control and analysis. The monitors were driven by a ZX1000 graphic controller (Artist Graphics Inc.), at 800×600, and a standard VGA controller, respectively.

In contrast to the above CRT-based displays, Warabi et al. (1986) used a laser-beam spot to indicate a subject's hand position together with a row of LEDs for displaying a step target. Similarly, Gibson et al. (1987) used a galvanometer-controlled laser spot to display smooth and step stimuli on a curved screen together with a white-light spot controlled by subject. Leist et al. (1987), Viviani and Mounoud (1990), and Klockgether (1994) also used galvanometer-controlled spots but via back-projection onto a curved screen, transparent digitizing table, and plexiglass surface, respectively. Van den Berg et al. (1987) used two rows of 240 LEDs each to display target and response. 2-D arrays of LEDs have also been used to indicate step targets in 2-D tracking tasks (Abend et al., 1982; Flash and Hogan, 1985).

However, graphics and display technologies have moved on substantially from the above heady days. Flat-screen LED displays have mostly replaced CRT-based displays, and high-resolution dual-screen color graphics built into motherboards are near standard in desktop and laptop computers. Similarly, the availability of powerful (and often open-source) graphics development software packages and libraries has greatly simplified the task of generating real-time dynamic graphics needed for tracking task displays.

Full-immersion 3-D virtual environments, via red/green glasses and green (left eye) and red (right eye) images rear-projected onto a large vertical screen (Mrotek et al., 2006) or a half-silvered mirror and stereoscopic glasses approach (Myall, 2008), have more recently opened up opportunities and applications for 3-D tracking.

While strictly not tracking tasks, driving simulators are often used instead of tracking tasks to provide a more realistic real-world environment, especially when one of the aims is, not surprisingly, to simulate the on-road task and environment (Banks et al., 2004; Lin et al., 2005; Desai and Haque, 2006; Lee, 2006; Schultheis et al., 2006, 2007; Cadeddu and Kondraske, 2007; Golz et al., 2007; Anund et al., 2008; Boyle et al., 2008; Lowden et al., 2009; Sommer et al., 2009; Boyle and Lee, 2010; Golz and Sommer, 2010; Jung et al., 2010; Sommer and Golz, 2010; Vadeby et al., 2010; Martens et al., 2011; Mayhew et al., 2011; Calhoun and Pearlson, 2012). Other than their more complex simulated real-road displays, the presence of distractors, and sometimes the presence of multiple tasks, a major distinguishing feature of driving simulators from tracking tasks is their substantial dead-zone within which the subject is not penalized as long as they keep within the lane markings or sides of the road. In many situations (e.g., driving) this is reasonably valid but, conversely, driving simulation is more difficult to score, with, for example, smaller deviations being ignored and the confounding presence of self-pacing. Notwithstanding, driving simulators are a valuable tool in driving research and driving assessment.

31.3.5 Target Signals

Tracking targets cover a spectrum from smoothly changing (low-bandwidth) targets, such as sinusoidal and random, through constant velocity ramp targets, to abrupt changing step targets.

31.3.5.1 Sinusoidal Targets

The periodicity, constancy of task complexity (over cycles), and spectral purity of sine targets make them valuable for measurement of within-run changes in performance (e.g., learning, lapses in concentration) (Jones and Donaldson, 1981), the study of ability to make use of the periodicity to improve tracking performance (Jones and Donaldson, 1989), and the study of the human frequency response (Leist et al., 1987). Several other workers have also used sine targets in their tracking tasks (Potvin et al., 1977; Miller and Freund, 1980; Ferslew et al., 1982; Notterman et al., 1982; Johnson et al., 1996; Soliveri et al., 1997; Heitger et al., 2004; Innes et al., 2007, 2009a; Siengsukon and Boyd, 2009a; Hoggarth et al., 2010).

Bloxham et al. (1984) and Frith et al. (1986) extended the use of sinewaves into a 2-D domain by having subjects track a moving circle on the screen.

31.3.5.2 Random Targets

These are commonly generated via a sum-of-sines approach in which a number of harmonically or nonharmonically related sinusoids of random phase are superimposed (Cassell et al., 1973; Neilson and Neilson, 1980; Miall et al., 1985; Baddeley et al., 1986; Frith et al., 1986; van den Berg et al., 1987; Barr et al., 1988; Cooper et al., 1989; Jones et al., 1993, 1996, 2002; Dalrymple-Alford et al., 1994, 2003; Hufschmidt and Lücking, 1995; Makeig and Jolley, 1996; Backs, 1997; Watson et al., 1997; Watson and Jones, 1998; Davidson et al., 2000, 2002; Heitger et al., 2004, 2007; Oytam et al., 2005; Peiris et al., 2006, 2011; Innes et al., 2007, 2009b; Huang et al., 2008; Poudel et al., 2009, 2010a,b; Hoggarth et al., 2010). If harmonically related, this can effectively give a flat spectrum target out to whatever bandwidth is required. Thus, in Jones et al.'s systems (Jones et al., 1993; Watson et al., 1997; Davidson et al., 2000; Peiris et al., 2006; Poudel et al., 2008; Innes et al., 2009b) the random signal generation program asks the user for the required signal bandwidth and then calculates the number of equal amplitude harmonics that must be summed together to give this bandwidth, each harmonic being assigned a randomly selected phase from a uniform phase distribution. Each target comprises 4096 (2^{12}) or more samples, a duration of at least 68 s (4096 samples/60.34 Hz), and a fundamental frequency of 0.0147 Hz (i.e., period of 68 s). By this means it is possible to have several different pseudo-random target signals that are nonperiodic up to 68-s duration, have flat spectra within a user-specified bandwidth, no components above this bandwidth, and whose spectra can be accurately computed by FFT from any 68-s block of target (or response). Another common approach to the generation of random targets is to digitally filter a sequence of pseudo-random numbers (Lynn et al., 1977; Potvin et al., 1977; Kondraske et al., 1984; van den Berg et al., 1987; Neilson et al., 1993; Neilson and Neilson, 2002), although this method gives less control over the spectral characteristics of the target. Bösser (1984) summed a number of these filtered sequences in such a way as to generate a target having an approximate $1/f$ spectrum. Another smooth pursuit target was generated by linking together short segments of sinewaves with randomly selected frequencies up to some maximum (Gibson et al., 1987) and was thus effectively a hybrid sinusoidal-random target.

In studies of lapses of responsiveness (e.g., microsleeps, lapses of sustained attention, lapses of focused attention), a 1-D target and most 2-D targets have "flat-spots" during which it is not possible to say definitively that a flat-spot in the response was due to a lapse (Peiris et al., 2006; Davidson et al., 2007; Huang et al., 2008). Poudel et al. (2008, 2009, 2010a,b) overcame this deficiency by designing a 2-D tracking task in which the speed of the target never goes below 20 mm/s (Figure 31.3); hence, a flat-spot in the tracking response can only be attributed to a true lapse of responsiveness.

31.3.5.3 Ramp Targets

Ramp targets have been used in conjunction with sensory gaps of target or response to study predictive tracking and ability to execute smooth constant velocity movements in the absence of immediate visual cues in normal subjects (Flowers, 1978b) and subjects with cerebellar disorders (Beppu et al., 1987), stroke (Jones et al., 1989), and Parkinson's disease (Cooke et al., 1978; Flowers, 1978a; Liu et al., 1999).

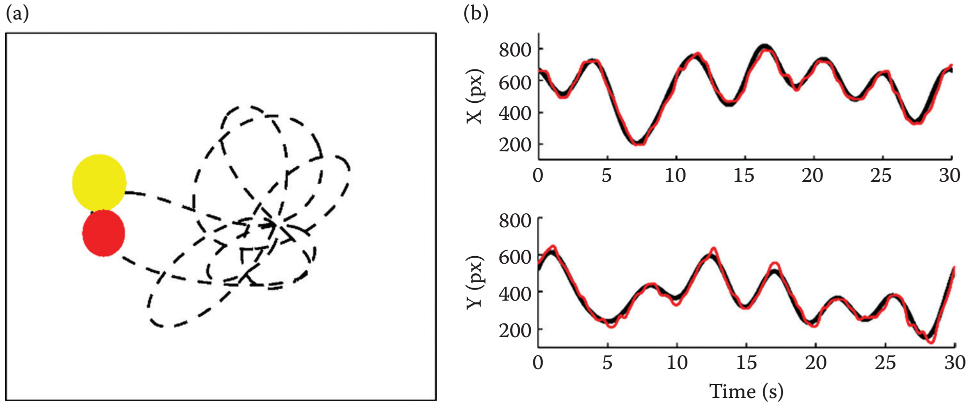

FIGURE 31.3 2-D random tracking task in which the speed of the target never goes below 20 mm/s, i.e., no flat-spots.

31.3.5.4 Step Targets

Step targets have been used in many applications and studies to measure and investigate abilities to predict, program, and execute ballistic (open-loop) movements. To enable this, spatial and temporal unpredictability have been incorporated into step tasks in various ways:

- *Temporal predictability*: The time of onset of steps has ranged from (a) explicitly predictable, with preview of the stimulus (Day et al., 1984; Jones et al., 1993), (b) implicitly predictable, with fixed interval between steps (Potvin et al., 1977; Cooke et al., 1978; Flowers, 1978b; Abend et al., 1982; Deuschl et al., 1996; Johnson et al., 1996; Sailer et al., 2002; Feys et al., 2005), to (c) unpredictable, with intervals between steps varied randomly over spans lying somewhere between 1.5 and 7.0 s (Angel et al., 1970; Flowers, 1978b; Kondraske et al., 1984; Anderson, 1986; Jones and Donaldson, 1986; Warabi et al., 1986; Gibson et al., 1987; Sheridan et al., 1987; Jones et al., 1993, 2002; Neilson et al., 1995; Watson et al., 1997; O'Dwyer and Neilson, 1998; Heitger et al., 2004; Allen et al., 2007; Innes et al., 2007, 2009a).
- *Amplitude predictability*: The amplitude of steps has ranged from (a) explicitly predictable, where the endpoint of the step is shown explicitly prior to the "Go" stimulus (Abend et al., 1982; Baroni et al., 1984; Sheridan et al., 1987; Jones et al., 1993; Deuschl et al., 1996; Watson et al., 1997; Feys et al., 2005), (b) implicitly predictable, where all steps have the same amplitude (Angel et al., 1970; Potvin et al., 1977; Cooke et al., 1978; Day et al., 1984; Kondraske et al., 1984; Anderson, 1986; Johnson et al., 1996; O'Dwyer and Neilson, 1998) or return-to-center steps in variable-amplitude step tasks (Flowers, 1976; Jones and Donaldson, 1986; Jones et al., 1993), to (c) unpredictable, with between 2 and 8 randomly distributed amplitudes (Flowers, 1976; Jones and Donaldson, 1986; Warabi et al., 1986; Gibson et al., 1987; Sheridan et al., 1987; Jones et al., 1993, 2002; Sailer et al., 2002; Heitger et al., 2004; Allen et al., 2007; Innes et al., 2007, 2009a).
- *Direction predictability*: Step tasks have had steps whose direction ranged from (a) all steps explicitly predictable, alternating between right and left (Flowers, 1976; Potvin et al., 1977; Cooke et al., 1978; Baroni et al., 1984; Kondraske et al., 1984; Johnson et al., 1996; O'Dwyer and Neilson, 1998; Sailer et al., 2002; Feys et al., 2005; Allen et al., 2007), or all in one direction (i.e., a series of discontinuous steps) (Sheridan et al., 1987), or between corners of an invisible square (Anderson, 1986), or having preview (Abend et al., 1982; Jones et al., 1993), (b) most steps predictable but with occasional "surprises" for studying anticipation (Flowers, 1978a), (c) a combination of unpredictable (outward) and predictable (back-to-center) steps (Angel et al.,

TABLE 31.1 Unpredictability in Step Tracking Tasks

		Temporal			Spatial-Amplitude			Spatial-Direction			Overall
		Full	Partial	None	Full	Partial	None	Full	Partial	None	Full
Angel et al. (1970)[a]	1-D	•				•		•		•	
Flowers (1976)[a]	1-D	•			•	•				•	
Potvin et al. (1977)	1-D		•			•				•	
Cooke et al. (1978)	1-D		•			•				•	
Flowers (1978a)	1-D		•			•			•		
Baroni et al. (1984)	1-D	•					•			•	
Day et al. (1984)	1-D			•		•		•			
Kondraske et al. (1984)	1-D	•				•				•	
Warabi et al. (1986)	1-D	•			•			•			•
Jones and Donaldson (1986)[a]	1-D	•			•	•		•		•	•
Gibson et al. (1987)	1-D	•			•			•			•
Sheridan et al. (1987)[a]	1-D	•			•		•			•	
Jones et al. (1993)[a]	1-D	•		•	•	•	•	•		•	•
Deuschl et al. (1996)	1-D		•				•			•	
Johnson et al. (1996)	1-D		•			•				•	
O'Dwyer and Neilson (1998)	1-D	•				•				•	
Sailor et al. (2002)	1-D		•			•				•	
Feys et al. (2005)	1-D		•				•			•	
Allen et al. (2007)[a]	1-D			•	•		•		•	•	
Abend et al. (1982)	2-D		•				•			•	
Anderson (1986)	2-D	•				•				•	
Watson et al. (1997)	2-D	•					•	•			
Ariff et al. (2002)	2-D		•			•			•		

[a] Several variations of unpredictability within one task or between multiple tasks.

1970; Jones and Donaldson, 1986; Jones et al., 1993; Watson et al., 1997), and (d) all steps unpredictable, with multiple endpoints (Warabi et al., 1986; Gibson et al., 1987) or resetting between single steps (Day et al., 1984).

The three elements of unpredictability can be combined in various ways to generate tasks ranging from completely predictable to completely unpredictable (Table 31.1). Several groups have implemented several variations of unpredictability both within and between step tracking tasks to investigate the possible loss of ability to use predictability to improve performance in, for example, Parkinson's disease (Flowers, 1978a; Sheridan et al., 1987; Watson et al., 1997). In addition to unpredictability, other characteristics can be built into step tasks including explicit target zones (Sheridan et al., 1987) and visual gaps in target (Flowers, 1976; Warabi et al., 1986).

An example of a 1-D step tracking task possessing full spatial and temporal unpredictability is that of Jones and colleagues (Jones and Donaldson, 1986; Jones et al., 1993; Heitger et al., 2004; Innes et al., 2007, 2009a) (Figure 31.4a). The task comprises 32 abrupt steps alternating between displacement from and return to center screen. In the nonpreview form, spatial unpredictability is present in the outward steps through four randomly distributed amplitude/direction movements (large and small steps requiring 90.0 and 22.5 deg on a steering wheel, respectively, and both to right and left of center) with temporal unpredictability achieved via four randomly distributed durations between steps (2.8, 3.4, 4.0, 4.6 s). This

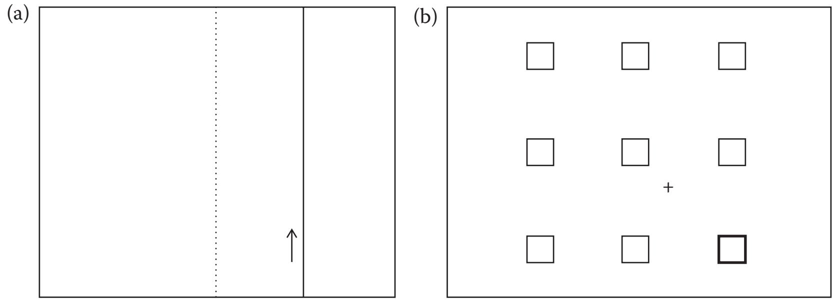

FIGURE 31.4 Visual displays for (a) 1-D step tracking task and (b) 2-D step tracking task (bottom-right square is current target).

task has been used, together with preview random tracking, to demonstrate deficits in sensory-motor control in the asymptomatic "good" arm of subjects who have had a unilateral stroke (Jones et al., 1989).

Watson et al. (1997) provided an example of a 2-D step tracking task with spatial and temporal unpredictability. In this task the subject must move a cross from within a central starting square to within one of eight 10-mm × 10-mm target squares that appear on the screen with temporal and spatial unpredictability (Figure 31.4b). The centers of the eight surrounding targets are positioned at the vertices and midway along the perimeter of an imaginary 100-mm × 100-mm square centered on the central square. To initiate the task, the subject places the cross within the perimeter of the central target. After a 2.0–5.0-s delay, one of the surrounding blue targets turns green and the subject moves the cross to within the green target square as quickly and as accurately as possible. After a further delay, the central target turns green indicating onset of the spatially predictive "back-to-center" target. The task, which comprises ten outward and ten return targets, was used to show that Parkinsonian subjects perform worse than matched controls on all measures of step tracking but are not impaired in their ability to benefit from spatial predictability to improve performance.

Step tasks with explicit target zones, in 1-D (Sheridan et al., 1987) or 2-D (Watson et al., 1997), provide the possibility of altering task difficulty by varying the size of the target. On the basis that subjects need only aim to get their marker somewhere within target zone (cf. close to center) then, according to Fitts's (1954) ratio rule, the difficulty of the primary movement is proportional to $\log_2(2A/W)$, where A is the amplitude of the movement and W is the width of the target.

31.3.5.5 Switching Targets

Jones et al. (1986, 1989, 1993) combined two quite different modes of tracking within a single task. Combination tracking involves alternating between preview random and nonpreview step tracking over 11-s cycles (Figure 31.5). Thus, while tracking the random target, the preview signal is abruptly and unpredictably replaced by a stationary vertical line at some distance from the random signal, and vice versa. Although the steps occur with a fixed fore-period (as with the step tasks listed above with implicit temporal predictability) of 7.3 s, subjects are not informed of this and, irrespective, Weber's law (Fitts and Posner, 1967) indicates the accuracy of prediction of steps with such a long pre-stimulus warning is very low. Combination tracking allows the study of ability to change *motor set* (Robertson and Flowers, 1990) between quite different modes of tracking and is analogous to having to quickly and appropriately respond to an unexpected obstacle, such as a child running onto the road, while driving a vehicle.

31.3.6 Dimensionality

The number of dimensions of a tracking task usually refers to the number of Cartesian coordinates in which the *target* moves, rather than those of the response marker or sensor handle, or the number of degrees of freedom of the target or of the upper limb. For example, (1) even with a 2-D joystick sensor

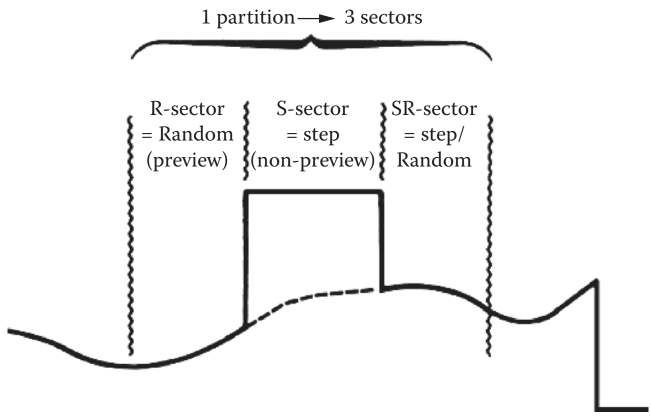

FIGURE 31.5 Section of input waveform in combination tracking in which the target alternates between preview-random and non-preview-step.

or light-pen, if the target moves in the vertical direction only (Neilson and Neilson, 1980; Kondraske et al., 1984; Miall et al., 1985; Jones et al., 1993), the task is only considered 1-D, irrespective of whether the response marker is confined to vertical movements on the screen or not; (2) if the target trajectory is a circle (Bloxham et al., 1984), the task is 2-D despite the target having only one degree of freedom (i.e., radius *r* is constant); and (3) a pursuit rotor is a 2-D task as it has a target which moves in two dimensions (whether Cartesian or polar) as well as doing so with two degrees of freedom (Welford, 1968).

Watson and Jones (1998) compared random 2-D with 1-D performance but in doing so scaled their 2-D target down so as to have an average displacement and velocity equal to that of its 1-D horizontal and vertical components. By this means they were able to unequivocally demonstrate that there is poorer performance on 2-D tasks and that this is due to both the increased dimensionality and increased position/speed demands of an unscaled 2-D task. Conversely, Oytam et al. (2005) showed that a 2-D tracking task has a response delay no longer than a 1-D task in healthy subjects.

Dual-axis tracking is a variant of 2-D tracking in which the 2-D task comprises two simultaneous orthogonal 1-D tasks in which one or more of the target, input device, control dynamics, and on-line feedback are different between the two axes. It has been used to investigate mechanisms and characteristics of 2-D tracking, and it has been shown that a 2-D task is indeed a single task rather than two separate orthogonal tasks (Navon et al., 1984; Fracker and Wickens, 1989).

More recently, virtual visuoperceptual environments combined with LED or electromagnetic 3-D trackers have provided a means for moving tracking tasks into the realm of 3-D (Mrotek et al., 2006; Myall et al., 2008).

31.3.7 Tracking Mode

The two primary modes of tracking—compensatory and pursuit—were introduced in Section 31.3.2 and Figure 31.1. Most tasks are of the pursuit type, which reflects its greater parallel with real-world sensory-motor tasks, but the compensatory task, in which the subject sees only the instantaneous value of the error signal, has proven valuable in several studies (Vince, 1948; Garvey, 1960; Potvin et al., 1977; Miller and Freund, 1980; Bösser, 1984; Barr et al., 1988; Makeig and Jolley, 1996; Backs, 1997; Huang et al., 2008; Gazes et al., 2010). The compensatory mode can be preferentially chosen for control-theory modeling due to its simpler set of defining equations (Potvin et al., 1977). Makeig and Jolly (1996) developed a novel variation to the standard compensatory tracking task by superimposing on the random target a second "force" equivalent to the force of gravity so as to cause the response disc to slip on an unseen slippery surface.

The preview task (Poulton, 1964; Welford, 1968; Potvin et al., 1977; Jones and Donaldson, 1986, 1989; Gianutsos, 1994; Jones et al., 1996, 2002; Kisacanin et al., 2000; Dalrymple-Alford et al., 2003; Heitger et al., 2004; Peiris et al., 2006; Innes et al., 2007, 2009a; Hoggarth et al., 2010) is an important variation of pursuit tracking in which a still greater correspondence with everyday tasks is achieved.

31.3.8 Controlled System Dynamics

It is well established that subjects can deal satisfactorily with a variety of tracking systems incorporating different control characteristics (Poulton, 1974; Neilson et al., 1995). Notwithstanding, the majority of tracking tasks have a zero-order controlled system in which the position of the response marker is proportional to the position of the sensor and the mechanical characteristics of friction, inertial mass, and velocity damping are simply those of the input device. Van den Berg et al. (1987) eliminated even these by feeding back a force signal from a strain gauge on the tracking handle to the power amplifier of a torque motor connected to their sensor. Conversely, Neilson et al. (1993) artificially introduced mechanical characteristics into the movement of their response marker by having a linear second-order filter as the controlled system; by an appropriate transfer function ($H(z) = 0.4060/(1 - 1.061z^{-1} + 0.4610z^{-2})$), they were able to introduce inertial lag and under-damping (resonant peak at 2.0 Hz). Miall et al. (1985) and Myall et al. (2008) introduced delays between their sensor and the displayed response so that they could study the effect of delayed visual feedback on performance. Soliveri et al. (1997) used both first-order (velocity) and zero-order (position) linear control dynamics to investigate differences in learning between parkinsonian and control subjects and between on- and off-medication. Navon et al. (1984) used a combination of velocity and acceleration control dynamics in their study on dual-axis tracking. Nonlinear transfer functions, such as second-order Volterra (fading memory) nonlinearities, have also been used in tracking controlled systems, primarily as a means for investigating adaptive inverse modeling mechanisms in the brain relating to voluntary movement (Davidson et al., 2000, 2002; Ghous and Neilson, 2002).

Controlled system dynamics can also be changed during a task. In "critical tracking," a novel variation of pursuit tracking conceived by Jex (1966), the delay of the controlled system increases during the task. There is no external target but instead the subject's own instability acts as an input to an increasingly unstable controlled system, $Y(s) = K\lambda/(s - \lambda)$, in which the level of instability, represented by the root λ (= $1/T$), is steadily increased during the task until a preset error is exceeded. The task has been described as analogous to driving a truck with no brakes down a hill on a winding road (Potvin et al., 1977). The task has been applied clinically (Potvin et al., 1977; Kondraske et al., 1984; Behbehani et al., 1988) and shown to be a reliable measure of small changes in neurological function. Alternatively, gain-change step tracking (Neilson et al., 1995), in which the gain of the control-display relation is increased or decreased without warning, has been used to investigate adaptive mechanisms in healthy subjects (O'Dwyer and Neilson, 1998; Myall, 2010) and those with Parkinson's disease (Myall, 2010).

Having a torque motor as part of the sensor opens up several new possibilities. It can be operated as a "torque servo," in which applied torque is independent of position (Kondraske et al., 1984), or a "position servo," in which applied torque is proportional to position error (together with velocity damping if desired) (Thomas et al., 1976). By adding external force perturbations, it is possible to measure and study neuromuscular reflexes and limb transfer function (i.e., stiffness, viscosity, and inertia), such as by applying constant velocity movements (Kondraske et al., 1984) or pulsatile (van den Berg et al., 1987), sinusoidal (Gottlieb et al., 1984), or random (Kearney and Hunter, 1983; van den Berg et al., 1987) force perturbations. Alternatively, the torque motor can be used to alter controlled-system characteristics in tracking tasks for studies and/or improvement of voluntary movement. For example, van den Berg et al. (1987) cancelled unwanted controller characteristics. Chelette et al. (1995) used "force reflection" to improve tracking performance in both normal subjects and those with spasticity, and Johnson et al. (1996) used antiviscous loading to investigate the cause of poor tracking in patients with Parkinson's disease.

31.3.9 Sensor-Display Compatibility

It is generally accepted that the level of compatibility between sensor and display in continuous tracking tasks influences the accuracy of performance (Neilson and Neilson, 1980). The perfectly compatible sensor is the display marker itself (Poulton, 1974) where the subject holds and moves the response marker directly such as with a light-pen in tracking (Neilson and Neilson, 1980), rotary pursuit (Welford, 1968; Schmidt, 1982), handle on a two-joint mechanical arm (Abend et al., 1982), self-paced 2-D tracing tasks (Driscoll, 1975; Stern et al., 1984; Hocherman and Aharon-Peretz, 1994; Gowen and Miall, 2006; Reithler et al., 2006), direct 2-D tracking on a touch-sensitive screen (Engel and Soechting, 2000), or 3-D tracking tasks in a virtual environment (Mrotek et al., 2006; Myall et al., 2008). Similarly, van den Berg et al. (1987) achieved a high sensor-display compatibility by having the LED arrays for target and response displayed directly above a horizontally moving handle. However, the majority of tracking tasks have sensors which are quite separate from the response marker displayed on an oscilloscope or computer screen. Sensor-display compatibility can be maximized in this case by having the sensor physically close to the display, moving in the same direction as the marker, and with a minimum of controlled system dynamics (e.g., zero-order). In the case of a joystick in a 2-D task, for example, direct compatibility (*Left–Right* → *Left–Right*) is easier than inverse compatibility (*Left–Right* → *Right–Left*), which is easier than noncompatibility (*Left–Right* → *Up–Down*). In contrast, fore-aft movements on a joystick appear to possess bidirectional compatibility in that *Fore–aft* → *Up–Down* seems as inherently natural as *Fore–aft* → *Down–Up* (i.e., no obvious inverse).

Sensor-display compatibility may not, however, be overly critical to performance. For example, Neilson and Neilson (1980) found no decrement in performance on random tracking of overall error scores, such as mean absolute error, between a light pen and a 1-D joystick; nevertheless, the latter did result in a decrease in gain, an increase in phase lag, and an increase in the noncoherent response component. Conversely, normal subjects find incompatible 2-D tracking very difficult to perform, taking up to 4 h of practice to reach a level of performance equal to that seen on pre-practice 2-D compatible tracking (Neilson et al., 1998).

31.3.10 Response Sampling Rates

Although some workers have manually analyzed tracking data from multichannel analog chart recordings (Flowers, 1976; Beppu et al., 1984) or analog-processed results (Potvin et al., 1977), the majority have used computers, sometimes via a magnetic tape intermediary (Flowers, 1978a; Day et al., 1984; Miall et al., 1985), to digitize data for automated analyses. Sampling rates used have varied from 10 Hz (Neilson and Neilson, 1980), through 20 Hz (Cooper et al., 1989; Neilson et al., 1993, 1998), 28.6 Hz (Jones and Donaldson, 1986), 30.2 Hz (Watson et al., 1997; Watson and Jones, 1998), 40 Hz (Frith et al., 1986), 60 Hz (Viviani and Mounoud, 1990), 60.3 Hz (= screen's vertical interrupt rate) (Viviani and Mounoud, 1990; Jones et al., 1993; Poudel et al., 2008, 2010b), 66.7 Hz (O'Dwyer and Neilson, 1998), 100 Hz (Abend et al., 1982; Stern et al., 1984; Hocherman and Aharon-Peretz, 1994; Jasper et al., 2010), to as unnecessarily high as 240 Hz (Myall et al., 2008), 250 Hz (Day et al., 1984), and 500 Hz (Feys et al., 2005).

For the most part, a relatively low sampling rate is quite satisfactory for analysis of tracking performance as long as the Nyquist criterion is met and there is appropriate analog or digital low-pass filtering to prevent aliasing. Spectral analysis indicates that the fastest of voluntary arm movements have no power above about 8–7 Hz (Jones and Donaldson, 1986). This is very similar to the maximal voluntary oscillations of the elbow of 4–6 Hz (Neilson, 1972; Leist et al., 1987) and to maximum finger tapping rates of 6–7 Hz (Muir et al., 1995). The sampling rate can be reduced still further if the primary interest is only of *coherent* performance, whose bandwidth is only of the order of 2 Hz for both kinesthetic stimuli (Neilson, 1972) and visual stimuli (Leist et al., 1987; Neilson et al., 1993); that is, performance above 2 Hz must be open-loop and, hence, learned and pre-programmed (Neilson, 1972). Thus, from an information theory point of view, there is no need to sample tracking performance beyond, say, 20 Hz.

However, a higher rate may well be justified on the grounds of needing better temporal resolution than 50 ms for transient or cross-correlation analysis, unless one is prepared to regenerate the signal between samples by some form of interpolation (e.g., sinc, spline, polynomial).

31.3.11 Divided-Attention Tasks

Jones and Pollock (2004) developed a divided-attention task (or dual-task) in which the subject has to divide their attention between two simultaneously performed tasks: a continuous visuomotor *Preview-Random Tracking* task and an intermittent visuoperceptual *Arrows Perception* task (Figure 31.6). Prior to the dual task, the subject is tested separately on the tracking and arrows perception tasks so as to obtain baseline performance data from which degradation of performance on each of the tasks when performed concurrently can be quantified. This divided-attention task has proven of particular value as one of the tests in off-road driving assessment of healthy older subjects (Hoggarth et al., 2010) and persons with neurological disorders (Innes et al., 2007, 2009b; Hoggarth, 2011).

Other implementations of divided-attention tasks also have continuous random tracking as the primary task but with a concurrent memory task (van Eekelen and Kerkhof, 2003; Jasper et al., 2010), concurrent digit span task (Baddeley et al., 1986; Dalrymple-Alford et al., 1994), concurrent auditory odd-ball task (Backs, 1997), or an intermittent visual detection task (Gazes et al., 2010), the latter being used to investigate the existence of competition for a capacity-limited “bottle-neck” stage.

31.3.12 Other Measures

Several researchers have further extended the information which can be derived from upper-limb tracking performance by comparison with other simultaneously recorded biosignals. The most common of these is the EMG, particularly integrated EMG due to its close parallel to force of contraction (Neilson, 1972) and where the tracking movement is constrained to be around a single joint. The EMG has been used together with step tracking for fractionating reaction times into premotor and motor components

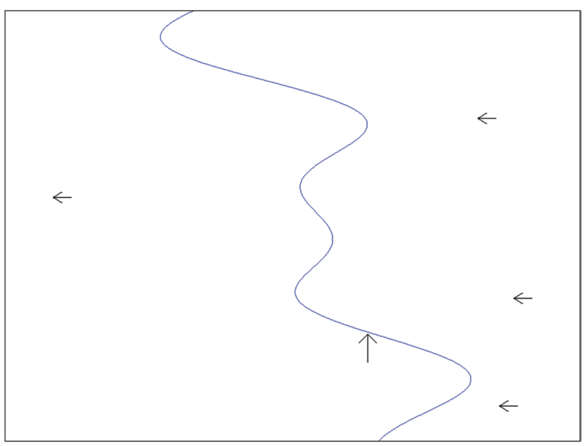

FIGURE 31.6 Divided-attention task (or dual-task) in which subjects have to divide their attention between two simultaneously performed tasks: a continuous *Preview-Random Tracking* task and an intermittent *Arrows Perception* task. While tracking the preview-random target (8.0-s preview) with a steering wheel, 12 consecutive sets of four arrows are displayed on the same screen (for 4.8 s, with 1.0 s between sets) and the subjects aim to maintain accurate tracking of the target while scanning the arrows and determining whether or not all 4 arrows are pointing in the same direction.

(Anson, 1987; Sheridan et al., 1987) and confirmation of open-loop primary movements (Sittig et al., 1985; Sheridan et al., 1987). In smooth tracking, correlation/cross-spectral analysis between the EMG and limb position has been used to study limb dynamics (Neilson, 1972; Barr et al., 1988).

In contrast, Cooper et al. (1989) measured the EEG at four sites during 2-D random tracking to show that slow changes in the EEG (equivalent to the Bereitschafts potential preceding self-paced voluntary movement), particularly at the vertex, are correlated with the absolute velocity of the target.

Simultaneous measurement of hand and eye movements has been undertaken by several researchers to investigate aspects of coupling between eye and hand movements. Eye movements were measured via electrooculography (horizontal only) (Warabi et al., 1986; Leist et al., 1987) or the infra-red limbus reflection technique (Gibson et al., 1987; Sailer et al., 2002; Feys et al., 2005). Interestingly, Leist et al. (1987) found that ocular pursuit and self-paced oscillations were limited to about 1.0 and 2.2 Hz, respectively, whereas the equivalent values for arm movements are 2 and 4–6 Hz, respectively.

31.3.13 Standard Assessment Procedures

Having designed and constructed a tracking task or set of tracking tasks with the characteristics necessary to allow measurement of the sensory-motor control performance under investigation, it is essential that this process be complemented by a well formulated set of standard assessment procedures. These must include (a) standard physical setup, in which positioning of subject, sensor, and screen are tightly specified and controlled, as well as factors such as screen brightness, room lighting, and so on and (b) standardized instructions. The latter are particularly important in tasks where speed-accuracy tradeoff (Fitts, 1954; Agarwal and Logsdon, 1990; Murata and Iwase, 2001; Battaglia and Schrater, 2007; Jax et al., 2007; Helton et al., 2009; Bye and Neilson, 2010) is possible. This applies particularly to step tracking, in which leaving the tracking strategy completely up to subjects introduces the possibility of misinterpretation of differences in performance on certain measures, such as reaction time, rise time, and mean absolute error. For example, subjects need to know if it is more important to have the initial movement end up close to the target (i.e., emphasis on accuracy of primary movement) or to get within the vicinity of the target as soon as possible (i.e., emphasis on speed of primary movement); the latter results in greater under/overshooting but also tends to result in lower mean errors). The most common approach taken is to stress the importance of both speed and accuracy with an instruction to subjects of the form: "Follow the target as fast and as accurately as possible."

31.3.14 Test and Experimental Protocols

The design of appropriate test and experimental protocols is also a crucial component of the tracking task design process (Pitrella and Kruger, 1983). When comparisons are made between different subjects, tasks, and/or conditions, careful consideration needs to be given to the paramount factors of *matching* and *balancing* to minimize the possibility of significant differences being due to some bias or confounding variable other than that under investigation. Matching can be achieved between experimental and control subjects in an inter-subject design by having average or paired equivalence on age, gender, education, and so on, or through an intra-subject design in which the subjects act as their own control in, say, a study of dominant versus nondominant arm performance. Balancing is primarily needed to offset *order effects* due to learning which pervade much of sensory-motor performance (Welford, 1968; Poulton, 1974; Schmidt, 1982; Frith et al., 1986; Jones et al., 1990). A study by Jones and Donaldson (1989) provides a good example of the application of these principles. Their study, aimed at investigating the effect of Parkinson's disease on predictive motor planning, involved 16 Parkinsonian subjects and 16 age- and sex-matched control subjects. These were then divided into eight subgroups in a three-way randomized cross-over design so as to eliminate between- and within-session order effects in determining the effect of target type, target preview, and medication on tracking performance.

31.4 Analysis of Sensory-Motor Performance

Analyses of raw tracking data provide performance information which is objective and quantitative and which can be divided into two broad classes:

- Measures of global (or overall or integrated) accuracy of performance.
- Measures of characteristics of performance.

31.4.1 Measures of Global Accuracy of Performance

The most commonly used measure of global or overall accuracy is the *mean absolute error* (MAE) (Poulton, 1974; Jones and Donaldson, 1986), which indicates the average distance the subject was away from the target irrespective of side; it is also variously called average absolute error (Poulton, 1974), modulus mean error (Poulton, 1974), mean rectified error (Neilson and Neilson, 1980), and, simply, tracking error (Kondraske et al., 1984; Behbehani et al., 1988). In contrast, the mean error, or constant position error, is of little value as it simply indicates only the extent to which the response is more on one side of the target than the other (Poulton, 1974). Measures of overall performance which give greater weighting to larger errors include mean square error (Neilson et al., 1993), root mean square error (McRuer and Krendel, 1959; Poulton, 1974; Navon et al., 1984; O'Dwyer and Neilson, 1995), variance of error (Neilson and Neilson, 1980), and standard deviation of error (Poulton, 1974). Relative or normalized error score equivalents of these can be calculated by expressing the raw error scores as a percentage of the respective scores obtained had subject simply held the response marker stationary at the mean target position (Poulton, 1974; Neilson and Neilson, 1980; Day et al., 1984); that is, No-Response = 100%. Alternatively, the relative root mean square error, defined as the square root of the ratio of the mean square value of the error signal to the mean square value of the target signal expressed as a percentage, allows tracking errors to be compared across tests using different target signals (Neilson et al., 1998).

Overall coherence is an important alternative to the above measures when it is wished to assess the similarity between target and response waveforms but there is a substantial delay between them. It provides an estimate of the proportion of the response that is correlated with the target over all frequencies (O'Dwyer and Neilson, 1995; O'Dwyer et al., 1996).

An issue met in viewing error scores from the perspective of Kondraske's elemental resource model (1995, 2006a,b) is the unifying requirement of its associated *general systems performance theory* (*GSPT*) that all dimensions of performance must be in a form for which a higher numerical value indicates a superior performance. Thus, scores which state that a *smaller* score indicates a superior performance, including reaction times, movement times, and all error scores, need to be transformed into *performance scores*. For example:

- Central response speed = 1/(reaction time)
- Information processing speed = 1/(8-choice reaction time)
- Movement speed = 1/(movement time)
- Tracking accuracy = 1/(tracking error)

As transformation via inversion is nonlinear, the distributions of raw error scores and derived performance will be quite different. This has no effect on ordinal analyses, such as nonparametric statistics, but will have some effect on linear analyses, such as parametric statistics, linear regression/correlation, and so on, and may include improvements due to a possible greater normality of the distributions of derived performances. An alternative transformation which would retain a linear relationship with the error scores is

- Tracking accuracy (%) = 100 – Relative tracking error

However, while this gives a dimension of performance with the desired "bigger is better" characteristic, it also raises the possibility of negative values, implying an accuracy worse than zero!—the author can attest to some subjects ending up with error scores worse than the hands–off score. Irrespective of GSPT, there is no doubt that it is beneficial to deal conceptually and analytically with multiple performance measures when *all* measures are consistently defined in terms of "bigger is better."

Time on target is a much cruder measure of tracking performance than all of the above but it has been used reasonably widely due to it being the result obtained from the pursuit rotor. The crudeness generally reflects (a) a lack of spatiotemporal sampling during a task (i.e., simple summation of time on target only) preventing the possibility of further analysis of any form, and (b) a task's performance *ceiling* due to the target having a finite zone within which greater accuracy, relative to center of zone, is unrewarded. This latter factor can, however, be used to advantage for the case where the investigator wishes to have control over the *difficulty* of a task, to gain, for example, similar levels of task difficulty across subjects irrespective of individual ability. This attribute has been used very effectively with 2-D random tracking tasks to minimize the confounding effects of major differences in task load between experimental and control subjects in dual-task studies of impairment of central executive function in subjects with Alzheimer's disease (Baddeley et al., 1986) and Parkinson's disease (Dalrymple-Alford et al., 1994).

31.4.2 Measures of Characteristics of Performance

Measures of global accuracy of tracking performance can detect and quantify the presence of abnormal sensory-motor control performance capacities with considerable sensitivity. Conversely, they are unable to give any indication of which of the many subsystems or performance resources in the overall sensory-motor system are, or may be, responsible for the abnormal performance. Nor can they provide any particular insight into the underlying neuromuscular control mechanisms of normal or abnormal performance.

Four approaches can be taken to provide information necessary to help identify the sensory-motor subsystems and their properties responsible for the *characteristics* of observed normal and abnormal performance:

- *Batteries of neurologic* sensory-*motor tests*: These tests can be used to, at least ideally, isolate and quantify the various sensory, motor, cognitive, and integrative functions and subsystems involved in sensory-motor performance as measured globally by, for example, tracking tasks.
- *Functional decomposition*: Fractionation of the various performance resources contributing to tracking performance.
- *Traditional signal processing approaches*: Time domain (ballistic and nonballistic) and frequency domain techniques.
- *Graphical analysis*: This has primarily been developed for measurement and investigation of changes in performance and underlying performance resources over time.

31.4.3 Batteries of Neurologic Sensory-Motor Tests

Potvin and colleagues (1975, 1985), now led by Kondraske et al. (1984, 2006), have developed an impressively comprehensive battery of tests for quantitative evaluation of neurologic function, covering a number of sensory, motor, cognitive, and sensory-motor functions and performance resources. Similarly, Jones and colleagues (Jones et al., 1993, 2002; Heitger et al., 2007; Innes et al., 2009a) have developed a battery of computerized sensory-motor and cognitive tests (*SMCTests*™) which, in addition to several tracking tasks, includes tests of component performance resources including visuoperception, nontracking visuomotor ability (ballistic movements, static and dynamic steadiness), complex attention, visual search, decision making, impulse control, planning, and divided attention. Many of these tests have been specifically designed to isolate and quantify the various performance resources involved in tracking tasks and in driving. There is, therefore, a close resemblance between some of the component tests and the tracking tasks, and between several tests and on-road driving, so as to maximize the validity of inter-test comparisons.

31.4.4 Functional Decomposition of Tracking Performance

There are three main approaches whereby tracking performance can be fractionated or decomposed into its functional components: sensory, perceptual, cognitive, motor planning, and motor execution.

The first approach involves breaking the ballistic response in step tracking into reaction time, movement time, overshoot, and settling time (Flowers, 1976; Jones and Donaldson, 1986; Behbehani et al., 1988; Watson et al., 1997) (see Section 31.4.6). This allows indirect deductions about cognitive, motor planning, and motor execution functions, although the distinction between cognitive and motor elements is often unclear.

The second approach involves calculation of differentials in tracking performance from inter-trial alterations in target and/or controlled system dynamics. This has been successfully used to demonstrate and study deficits in Parkinson's disease with respect to predictive motor planning (Flowers, 1978c, 1978a; Stern et al., 1983; Bloxham et al., 1984; Day et al., 1984; Sheridan et al., 1987; Jones and Donaldson, 1989; Soliveri et al., 1997; Watson et al., 1997) and acquisition/modification of motor sets (Frith et al., 1986), and increased reliance on visual feedback (Flowers, 1976, 1978a; Cooke et al., 1978; Warabi et al., 1988; Klockgether and Dichgans, 1994; Liu et al., 1999). This approach has also been used successfully to demonstrate and investigate internal inverse models in the brain (see Section 31.5.5).

The third approach allows a more direct identification of the contribution of certain elemental resources to tracking performance during a specific tracking run. For example, by introducing the concept of a visuoperceptual buffer zone, it is possible to estimate the contribution of visuoperceptual function to tracking performance (Jones et al., 1996). This technique has been used to demonstrate that impaired visuoperceptual function in Parkinsonian subjects plays only a minor role in their poor tracking performance (Jones et al., 1996) but, conversely, that impaired tracking performance in stutterers is predominantly due to reduced dynamic visuospatial perception (Jones et al., 2002). Furthermore, the visuoperceptual function can itself be fractionated into visual acuity, static perception, and dynamic perception (Jones and Donaldson, 1995).

31.4.5 Time-Domain Analysis of Tracking Performance: Nonballistic

There are several run-averaged biases which can indicate the general form of errors being made, particularly when the tracking performance is subnormal. Positive *side of target* (%) and *direction of target* (%) biases reflect a greater proportion of errors occurring to the right of the target or while the target is moving to the right, respectively (Jones and Donaldson, 1986) which, if substantial, may indicate the presence of some visuoperceptual deficit. Similarly, the *side of screen* bias (assuming mean target position is mid-screen) (Jones and Donaldson, 1986) is identical to the mean error or constant position error.

Perhaps the single most important measure of performance, other than mean absolute or RMS error, for nontransient targets is that of the average time delay, or *lag*, of a subject's response with respect to the target signal. The lag is most commonly defined as being the shift τ corresponding to the peak of the cross-correlation function, calculated directly in the time domain or indirectly via the inverse of the cross-spectrum in the frequency domain. Although simulation studies indicate that these techniques are at least as accurate and as robust to noise/remnants as the alternatives listed below (Watson, 1994), one needs to be aware of a bias leading to underestimation of the magnitude of the lag (or lead) due to distortion of the standard cross-correlation function, but specifically of the peak toward zero shift. The distortion arises due to the varying overlap of two truncated signals (i.e., the target and the response) resulting in the multiplication of the cross-correlation function by a triangle (maximum at $\tau = 0$ and zero at $\tau = NT_s$, assuming signals of equal length NT_s. This effect is minimal as long as both signals have a mean value of zero. Temporal resolution is another factor deserving consideration. If desired, greater resolution than that of the sampling period can be obtained by interpolation of the points around the peak of the cross-correlation function by some form of curve fitting (e.g., inverse parabola).

An alternative estimate of the lag, which has proven accurate on simulated responses, can be gained from the *least squares time delay estimation* by finding the time shift between the response and target at which the mean square error is minimized (Fertner and Sjölund, 1986; Jones et al., 1993; Innes et al., 2009a). Another approach, *phase shift time delay* estimation, calculates lag from the gradient of the straight line providing a best least squares to the phase points in the cross-spectrum (Watson et al., 1997). This *phase-correlation* technique has, however, proven more robust to noncorrelated remnants in the response than the other procedures (Watson, 1994).

Several measures used to help characterize within-run variability in performance include variance of error (Neilson and Neilson, 1980), standard deviation of error (Poulton, 1974), and inconsistency (Jones and Donaldson, 1986).

31.4.6 Time-Domain Analysis of Tracking Performance: Ballistic

Irrespective of any of the above nonballistic analyses, evaluation of step tracking performance usually involves separate ballistic or transient analysis of each of the step responses. This generally takes the form of breaking up each response into three phases (Figure 31.7): (1) reaction time phase, or the time between onset of step stimulus and initiation of movement defined by exit from a visible or invisible reaction zone, (2) primary movement phase, or the open-loop ballistic movement made by most normal subjects aiming to get within the vicinity of the target as quickly as possible, the end of which is defined as the first stationary point, and (3) secondary correction phase, comprising one or more adjustments and the remaining time needed to enter and stay within target zone. The step measures from individual

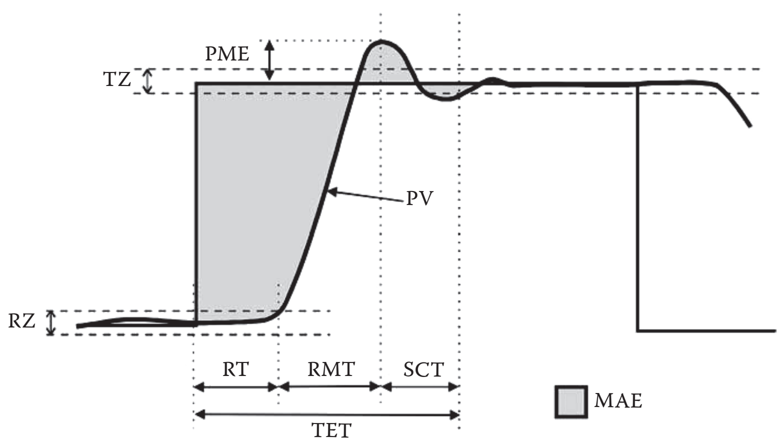

FIGURE 31.7 Transient response analysis. Tolerance zones: RZ is the reaction zone, and TZ is the target zone. Performance parameters: RT is the reaction time, PMT is the primary movement time, SCT is the secondary correction time, TET is the target entry time, PV is the peak velocity, PME is the primary movement error, and MAE is the mean absolute error over a fixed interval following stimulus.

steps can then be grouped into various step categories to allow evaluation of the effect of step size, spatial predictability, arm dominance, and so on, on transient performance.

Accuracy of the primary aimed movement can also be characterized in terms of a constant error and a variable error (standard deviation of error), which are considered to be indices of accuracy of central motor programming and motor execution, respectively (Guiard et al., 1983).

Phase-plane (velocity vs. position) plots provide an alternative means for displaying and examining the qualitative characteristics of step tracking responses. In particular, they have proven valuable for rapid detection of gross abnormalities (Potvin et al., 1985). Behbehani et al. (1988) introduced a novel quantitative element to phase-plane analysis by deriving an index of coordination [IN1] where V_m is the maximum velocity during an outward and return step and A is the area within the resultant loop on the phase-plane plot.

31.4.7 Frequency-Domain Analysis of Tracking Performance

Cross-correlation and spectral analysis have proven invaluable tools for quantifying the frequency-dependent characteristics of the human subject. The cross-spectral density function, or cross-spectrum $S_{xy}(f)$, can be obtained from the random target $x(t)$ and random response $y(t)$ by taking the Fourier transform of the cross-correlation function $r_{xy}(\tau)$, that is, $S_{xy}(f) = F[r_{xy}(\tau)]$, or in the frequency domain via $S_{xy}(f) = X(f)Y(f)^*$, or by a nonparametric system identification approach (e.g., "spa.m" in MATLAB®). The cross-spectrum provides estimates of the relative amplitude (i.e., gain) and phase-lag at each frequency. Gain, phase, and remnant frequency response curves provide objective measures of pursuit tracking behavior, irrespective of linearity, and are considered a most appropriate "quasi-linear" tool for obtaining a quantitative assessment of pursuit tracking behavior (Neilson and Neilson, 1980). From the cross-spectrum one can also derive the *coherence function* which gives the proportion of the response signal linearly related to the target at each frequency: $C_{xy}(f) = |S_{xy}(f)|^2/S_x(f)S_y(f)$, where $S_{xy}(f)$ is the cross-spectral density between $x(t)$ and $y(t)$, and $S_x(f)$ and $S_y(f)$ are the auto-spectral densities of $x(t)$ and $y(t)$, respectively. Lynn et al. (1977) emphasized, however, that one must be cognizant of the difficulty representing tracking performance by a quasi-linear time-invariant transfer function, especially if the run is of short duration or if the target waveform is of limited bandwidth, as the results can be so statistically unreliable as to make description by a second- or third-order transfer function quite unrealistic. Van den Berg et al. (1987) chose four parameters to characterize tracking performance: low-frequency performance via the mean gain of transfer function at the 3 lowest of 8 frequencies in target signal, high-frequency performance via the frequency at which the gain has dropped to less than 0.4, mean delay via shift of peak of the cross-correlation function, and remnant via power in frequencies introduced by subject relative to total power. Spectral and coherence analysis have been used to demonstrate (i) the human bandwidth is about 2 Hz for both kinesthetic tracking (Neilson, 1972) and visual tracking (Neilson et al., 1993), (ii) a much greater relative amplitude of the second harmonic in the response of cerebellar subjects in sine tracking (Miller and Freund, 1980), (iii) a near constant lag except at low frequencies in normal subjects (Cassell et al., 1973), (iv) adaptation to time-varying signals (Bösser, 1984), (v) formation of internal models of novel visuomotor relationships for feedforward control in the brain (Davidson et al., 2000) and confirmation, via simulations, of nonlinear control systems in the brain (Davidson et al., 2002), (vi) 2-D asymmetry in postural steadiness (Myklebust et al., 2009), and (vii) formation of non-dynamic and dynamic inter-limb synergies in a bimanual tracking task (O'Dwyer and Neilson, 1995).

31.4.8 Graphical Analysis of Tracking Performance

Most of the above analyses give quantitative estimates of some aspect of performance which is effectively assumed to be constant over time, other than for experimental and inter-session fluctuations. This is frequently not the case, especially for more complex sensory-motor tasks such as tracking. Changes in performance over time can be divided into two major classes:

- *Class I*—Owing to factors such as practice, fatigue, sleep deprivation, lapses of responsiveness, time of day, stimulants and depressants, lack of practice, and changes in task complexity, in which the underlying performance resources remain unchanged.
- *Class II*—Owing to factors in which there have been abrupt or gradual changes in underlying performance resources at one or more sites in the sensory-motor system due to aging, trauma, or pathology.

Studies of Class I factors using tracking tasks are complicated most by the intra-run *difficulty* of a task not being constant. Changes in tracking accuracy *during* a run can be viewed via graphs of target, response, and/or errors. The latter is particularly informative for sinusoidal targets for which the mean absolute errors can be calculated over consecutive epochs, corresponding to sine-wave cycles, and plotted both in a histogram form and as a smoothed version of this (Jones and Donaldson, 1981, 1986). As complexity of task is constant over short epochs (cf. random pursuit task), the error graph gives an accurate measure of a subject's time-dependent spatiotemporal accuracy that is not confounded by changes in task difficulty and, therefore, gives a true indication of changes in performance due to factors such as learning, fatigue, and lapses in concentration. However, the same can also be achieved for pseudo-random targets due to their periodicity over longer intervals, such as 128 s (Peiris et al., 2006) and 30 s (Poudel et al., 2008). This is of considerable value when time-on-task effects are required following extended continuous-tracking sessions, such as 60 min (Peiris et al., 2006) and 50 min (Poudel et al., 2010a).

Neilson et al. (1998) devised an alternative procedure for intra-run analysis, termed micro-movement analysis, based upon segmentation of the *X* and *Y* deflections of the response cursor on the basis of discontinuities, flat regions, and changes in direction of the response. They used this to identify changes in visuomotor coupling during the first 4 min of tracking on a 2-D compatible task following 4 h of practice on a 2-D incompatible task. They proposed that these changes are evidence of rapid switching between different sensory-motor models in the brain.

By comparison, as long as the task remains unchanged over successive runs, studies of class II factors using tracking tasks are complicated most by inter-run *learning*. Although most learning occurs over the first one or two runs or sessions, tracking performance can continue to improve over extended periods as evidenced by, for example, significant improvements still being made by normal subjects after nine weekly sessions (Jones and Donaldson, 1981). Consequently, a major difficulty met in the interpretation of serial measures of performance following acute brain damage is differentiation of neurologic recovery from normal learning. Furthermore, it is not simply a matter of subtracting off the degree of improved performance due to learning seen in normal control subjects. Jones et al. (1990) developed graphical analysis techniques which provide for the removal of the learning factor, as much as is possible, and which can be applied to generating recovery curves for individual subjects following acute brain damage such as stroke. They demonstrated that, for tracking, percentage improvement in performance (PIP) graphs give more reliable evidence of neurologic recovery than absolute improvement in performance (PIA) graphs due to the former's greater independence from what are often considerably different absolute levels of performance.

31.4.8 Statistical Analysis

Parametric statistics (*t*-tests, ANOVA, discriminant analysis) are by far the most commonly used in studies of sensory-motor/psychomotor performance due, in large part, to their ability to draw out interactions between dependent variables. However, there is often a strong case for using nonparametric statistics. For example, the Wilcoxon matched-pairs statistic may be preferable for both between-group and within-subject comparisons due to its greater robustness over its parametric paired *t*-test equivalent, with only minimal loss of power if data are parametric. This is important due to many sensory-motor measures having very skewed distributions as well as considerably different variances between normal and patient groups.

31.5 Applications

Tracking tasks provide objective and quantitative measures and characteristics of sensory-motor control performance and capacities which have proven invaluable in six main classes of applications:

- Clinical screening for sensory-motor deficits
- Neurology and rehabilitation research
- Human performance and factors research (healthy subjects)
- Vocational and recruitment screening
- Modeling and prediction of human performance
- Computational modeling of the human brain

31.5.1 Clinical Screening for Sensory-Motor Deficits

An excellent example of tracking tasks being used in clinical practice for the detection and/or quantification of sensory-motor deficits (arising from one or more lesions in one or more sites in the sensory-motor system) is that of providing objective measures in off-road driving assessment systems/programs (Jones et al., 1983; Croft and Jones, 1987; Gianutsos, 1994; Korteling and Kaptein, 1996; Fischer et al., 2002; Innes et al., 2007, 2011a; Hoggarth et al., 2010).

31.5.2 Neurology and Rehabilitation Research

Tracking tasks have been used extensively in research studies of neurological disorders and rehabilitation. They have been used to identify and/or quantify sensory-motor control deficits in:

- Parkinson's disease (Cassell et al., 1973; Cooke et al., 1978; Flowers, 1976, 1978a, 1978c; Stern et al., 1983; Baroni et al., 1984; Bloxham et al., 1984; Day et al., 1984; Frith et al., 1986; Stern, 1986; Warabi et al., 1986, 1988; Gibson et al., 1987; Sheridan et al., 1987; Behbehani et al., 1988, 1990; Stelmach and Worrington, 1988; Jones and Donaldson, 1989; Dalrymple-Alford et al., 1994; Hocherman and Aharon-Peretz, 1994; Klockgether and Dichgans, 1994; Watson, 1994; Hufschmidt and Lücking, 1995; Johnson et al., 1996; Soliveri et al., 1997; Watson et al., 1997; Gonzalez et al., 2000; Fischer et al., 2002; Allen et al., 2007)
- Stroke (Lynn et al., 1977; De Souza et al., 1980; Jones and Donaldson, 1981; Stelmach and Worrington, 1988; Jones et al., 1989, 1990; O'Dwyer et al., 1996; Fischer et al., 2002; Notley et al., 2007; Siengsukon and Boyd, 2009a,b)
- Traumatic brain injury (Jones and Donaldson, 1981; Korteling and Kaptein, 1996; Heitger et al., 2004, 2007; Innes et al., 2007)
- Cerebral palsy (Neilson et al., 1990, 1992)
- Cerebellar disorders (Beppu et al., 1984, 1987; Becker et al., 1991; Cody et al., 1993; Deuschl et al., 1996)
- Alzheimer's disease (Baddeley et al., 1986; Kisacanin et al., 2000; Hoggarth, 2011)
- Stuttering (Neilson, 1980; Neilson et al., 1992; Zebrowski et al., 1997; Jones et al., 2002)

There are also many examples of patients being assessed repeatedly on tracking tasks for periods up to 12 or more months. This has been done to quantify recovery following stroke (Lynn et al., 1977; De Souza et al., 1980; Jones and Donaldson, 1981; Jones et al., 1989, 1990) and traumatic brain injury (Jones and Donaldson, 1981; Heitger et al., 2004, 2007). Tracking tasks have also been used to quantify changes due to medication, such as in Parkinson's disease (Baroni et al., 1984; Johnson et al., 1996; Soliveri et al., 1997).

31.5.3 Human Performance and Factors Research

Tracking tasks have been used extensively in research studies of human performance in healthy subjects and, in particular, on *factors* having beneficial or detrimental effects on sensory-motor performance, such as:

- Learning by *practicing* the same task or similar tasks (Poulton, 1974; Notterman et al., 1982; Schmidt, 1982; Jones et al., 1986, 1990)
- Learning by *adapting* to major changes in the tracking task, such as in controlled system dynamics, sensor-display relationships, target signals, or visual display of target or response (O'Dwyer and Neilson, 1995; Backs, 1997; Foulkes and Miall, 2000; Davidson et al., 2002; Miall and Jackson, 2006)
- Age (Jones et al., 1986)
- Gender (Jones et al., 1986)
- Dimensionality (Watson and Jones, 1998)
- Time-of-day (Dalrymple-Alford et al., 2003; Jasper et al., 2010)
- Time-on-task (Welford, 1968; Potvin and Tourtellotte, 1975; Van Orden et al., 2000; Petrilli et al., 2005; Peiris et al., 2006; Poudel et al., 2010a)
- Alcohol (Dalrymple-Alford et al., 2003)
- Reduced alertness due to physical fatigue, mental fatigue, sleepiness, sleep deprivation, and/or trait propensity for excessive daytime sleepiness leading to impaired performance. Decrements in performance can range right from minimal (e.g., mildly drowsy) to complete lapses of responsiveness due to lapses of sustained attention, microsleeps (0.5–15 s), or nodding off (>15 s) (Makeig and Jolley, 1996; Peiris et al., 2006, 2011; Davidson et al., 2007; Huang et al., 2008; Poudel et al., 2008, 2010a; Jones et al., 2010)
- Loss of task-orientated attention due to distraction, which can be external or internal and voluntary or involuntary

31.5.4 Vocational and Recruitment Screening

The origin of tracking tasks actually goes back to World War II when they were developed and used to help screen and train aircraft pilots (Welford, 1968; Poulton, 1974). Since then, they have been used to a rather limited degree to determine suitability for recruitment into various vocations in terms of confirming a minimum level, or detecting a superior level, of sensory-motor performance capacity. There is considerable scope for much greater use of tracking tasks alongside psychometric tests as part of the recruitment process, particularly in the transport and defense sectors. They also have the potential to help identify persons with a trait for excessive daytime sleepiness and, even more so, a high propensity for microsleeps (Innes et al., 2010, 2011b) in occupations in which complete lapses of responsiveness can lead to fatal/multi-fatality accidents, such as in long-distance driving, aircraft piloting, air-traffic control, and train drivers.

31.5.5 Modeling and Prediction of Human Performance

Tracking tasks have played an important role in modeling and prediction of human performance. Thus, in contrast to fractionation of performance on a high-level task (e.g., tracking, driving) (see Section 31.4.4), Kondraske et al. (1995, 2006a, b, 2006) have developed techniques for the reverse process. They have shown how their hierarchical elemental resource model, together with *non-linear causal resource analysis* (NCRA), can be used to *predict* performance on high-level tasks from performance on a number of lower-level tasks (Vasta and Kondraske, 1994; Kondraske et al., 1997, 2002; Fischer et al., 2002; Gettman et al., 2003; Matsumoto et al., 2006; Kondraske and Stewart, 2009). This approach has considerable potential in application areas such as rehabilitation. For example, it has been used in driving assessment programs to predict on-road driving ability from performance on several key lower-level off-road/clinic-based tasks pertinent to driving, such as reaction time, visuospatial, cognitive, and tracking tasks (Fischer et al., 2002; Innes et al., 2007, 2009b; Hoggarth et al., 2010).

However, a caution: Innes et al. (2011a) compared the ability of six modeling approaches to predict driving ability (as assessed by driving occupational therapists blinded to off-road results) based on performance on a battery of sensory-motor and cognitive tests (*SMCTests*™) (see Section 31.4.3) in 501 people with brain disorders. At the classification level, they found that two kernel methods—support vector machine (SVM) and product kernel density (PK)—were substantially more accurate at classifying on-road pass or fail (SVM 99.6%, PK 99.8%) than the four other models—kernel product density (KP 81%), binary logistic regression (BLR 78%), discriminant analysis (DA 76%), and NCRA (74%). However, accuracy decreased substantially for all of the kernel models when cross-validation techniques were used to estimate prediction of on-road pass or fail in an independent referral group (SVM 76%, PK 73%, KP 72%) but decreased only slightly for BLR (76%) and DA (75%) (cross-validation of NCRA was not possible). From this, they concluded that, at least for this predictive problem, while kernel-based models are successful at modeling complex data at a classification level, this is likely to be due to overfitting of the data, which does not lead to an improvement in accuracy in independent data over and above the accuracy of other less complex modeling techniques.

31.5.6 Computational Modeling of the Human Brain

Through their continuous nature and versatility to incorporate different targets, different modes of tracking, different sensor-display compatibilities, control system dynamics, and so on, tracking tasks have proven a powerful experimental tool in helping develop, train, and validate computational models of the brain (Jex, 1966; Desmedt, 1978; Lynn et al., 1979; Bösser, 1984; Flash and Hogan, 1985; Neilson et al., 1992, 1998; Sriharan, 1997; Davidson et al., 1999, 2000, 2002; Engel and Soechting, 2000; Ariff et al., 2002; Ghous and Neilson, 2002; Neilson and Neilson, 2002, 2004; Miall and Jackson, 2006; Bye and Neilson, 2010). This includes experimental confirmation of the presence of internal inverse models (Davidson et al., 2000, 2002; Ghous and Neilson, 2002), investigations of intermittency (Vince, 1948; Miall et al., 1985; Neilson et al., 1988a; Foulkes and Miall, 2000; Oytam et al., 2005), investigations of the formation of synergies (O'Dwyer and Neilson, 1995; Neilson and Neilson, 2002; Oytam et al., 2005), and confirmation, rejection, or refinement of computational models of sensory-motor function (Neilson et al., 1988a, b, 1992, 1995, 1998; O'Dwyer and Neilson, 1995; Davidson et al., 2002; Ghous and Neilson, 2002; Miall and Reckess, 2002; Miall and Jackson, 2006).

Defining Terms

Accuracy of movement: The primary *dimension of performance* achieved by the *sensory-motor control* performance resource.

Basic element of performance: Defined by a *functional unit* and a *dimension of performance*, for example, right elbow flexor + speed.

Dimension of performance: A basic measure of performance such as speed, range of movement, strength, spatial perception, spatiotemporal accuracy.

Functional unit: A subsystem such as right elbow flexor, left eye, motor memory.

Performance capacity: The maximal level of performance possible on a particular dimension of performance.

Performance resource: One of a pool of elemental resources, from which the entire human is modeled (Kondraske, 2006a), and which is available for performing tasks. These resources can be subdivided into life sustaining, environmental interface, central processing, and skills domains, and have a parallel with *basic elements of performances*.

Sensor: [in context of tracking tasks] A device for measuring/transducing a subject's motor output.

Sensory-motor control: A primary *performance resource* responsible for overall sensory-motor performance and, in particular, the *dimension of performance* of *accuracy of movement*. The other performance resources on which accuracy of movement is also dependent are strength, reaction time, speed, steadiness, and so on.

Sensory-motor performance: Overall/integrated performance of the *sensory-motor system*, comprising multiple constituent performance resources and associated *dimensions of performance*, including strength, speed, reaction time, steadiness, visual acuity, visuoperception, and *sensory-motor control*.

Sensory-motor system: Comprises all performance resources responsible for all types of *sensory-motor performance*. Encompasses sensory systems (visual, auditory, proprioceptive, tactile), motor systems (muscles, neuromuscular pathways and reflexes, motor planning, motor execution and coordination), and many higher-level systems in the CNS (visuoperception, cognition, memory, central executive, arousal, attention, default mode, etc.).

Spatiotemporal accuracy: The class of accuracy most required by tasks which place considerable demand on attainment of simultaneous spatial and temporal accuracy. This refers particularly to *paced* tasks such as tracking, driving, ball games, and video games.

Tracking task: A laboratory apparatus and associated procedures which have proven one of the most versatile means for assessing and studying the human "black-box" *sensory-motor system* by providing a continuous record of a subject's response, via some *sensor*, to any one of a large number of continuous and well-controlled stimulus or target signals.

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