Functional Modelling of the Human Timing Mechanism

BY

GUY MADISON

Dissertation for the Degree of Doctor of Philosophy in Psychology presented at Uppsala University in 2001

ABSTRACT

Madison, G. 2001. Functional Modelling of the Human Timing Mechanism. Acta Universitatis Upsaliensis. *Comprehensive Summaries of Uppsala Dissertations from the Faculty of Social Sciences* 101. 77 pp. Uppsala. ISBN 91-554-5012-1.

Behaviour occurs in time, and precise timing in the range of seconds and fractions of seconds is for most living organisms necessary for successful interaction with the environment. Our ability to time discrete actions and to predict events on the basis of prior events indicates the existence of an internal timing mechanism. The nature of this mechanism provides essential constraints on models of the functional organisation of the brain.

The present work indicates that there are discontinuities in the function of time close to 1 s and 1.4 s, both in the amount of drift in a series of produced intervals (Study I) and in the detectability of drift in a series of sounds (Study II). The similarities across different tasks further suggest that action and perceptual judgements are governed by the same (kind of) mechanism. Study III showed that series of produced intervals could be characterised by different amounts of positive fractal dependency related to the aforementioned discontinuities.

In conjunction with other findings in the literature, these results suggest that timing of intervals up to a few seconds is strongly dependent on previous intervals and on the duration to be timed. This argues against a clock-counter mechanism, as proposed by scalar timing theory, according to which successive intervals are random and the size of the timing error conforms to Weber's law.

A functional model is proposed, expressed in an autoregressive framework, which consists of a single-interval timer with error corrective feedback. The duration-specificity of the proposed model is derived from the order of error correction, as determined by a semi-flexible temporal integration span.

Key words: Brain mechanisms, Brownian motion, drift, dynamical systems, fractal, human, fractional Gaussian noise, Hurst exponent, time, time series analysis, timing.

Guy Madison, Department of Psychology, Uppsala University, Box 1225, SE-751 42 Uppsala, Sweden

This thesis is based on the following papers, which will be referred to in the text by their Roman numerals:

I. Madison, G. (2001). Variability in isochronous tapping: higher-order dependencies as a function of inter tap interval. Journal of Experimental Psychology: Human Perception and Performance, *27*.

II. Madison, G. (2000). Modelling sensitivity for drift in auditory sequences. Manuscript submitted for publication.

III. Madison, G. (2001). Fractal modelling of human time production. Manuscript submitted for publication.

Reprints of figures were made with kind permission from Swets and Zeitlinger Publishers in Lisse, the Netherlands, and from the American Psychological Association, Washington, DC.

Contents

Abbreviations

$1/f$	One-over-f noise
α	Intercept (of a linear regression function)
A^2	Spectral power density
ANOVA	Analysis of variance
AR	Autoregressive
ARIMA	Autoregressive integrated moving average
β	Slope (of a linear regression function)
Bm	Brownian motion
CNS	Central nervous system
CV	Coefficient of variance
D	(Fractal) dimension
EC	Error correction
EEG	Electroencephalography
f	Frequency
fBm	Fractional Brownian motion
fGn	Fractional Gaussian noise
fMRI	Functional magnetic resonance imaging
H	Hurst exponent
IOI	Inter onset interval
ISIP	Isochronous serial interval production
ISMS	Isochronous sensorimotor synchronisation
k	Lag (of autocorrelation)
MA	Moving average
Md	Median
MIIL	Measured integration interval length
PEST	Parameter estimation by sequential testing
PET	Positron emission tomography
r_k	Autocorrelation coefficient for lag k
RD	Relative dispersion
S_{pe}	Proportion explained variance
Q	Inter-quartile range
Cov	Covariance
TIS	Temporal integration span

Introduction

Behaviour occurs in time. The lion's share of behaviours also occurs at precisely the right time to render them functional. This relative well-behavedness of biological timing, and the fact that the temporal dimension is ubiquitous and can not be neatly parcelled into a subdiscipline of its own are but two possible reasons why timing has not been systematically addressed by the life sciences. However, mounting efforts to understand the structural and functional organisation of the brain stresses the need to incorporate time into any comprehensive model. The most fundamental questions from this perspective are by what principle any mechanism capable of measuring out time intervals operates, if the timing of an organism is governed by one or several such mechanisms, whether these mechanisms are general or related to a certain modality or mode of behaviour, and where and how they are implemented in the neural system.

The core of the arguments will be concerned with two issues that have been advanced by recent work, and which stand out as particularly pertinent for understanding human timing. The first issue is duration-specificity, which refers to the neural system's performance as a function of time, that is, the duration of the intervals processed. Serial dependency is the second issue, which refers to the fact that a given interval is typically influenced by preceding intervals. When intervals are produced or judged in a sequence where the end of one interval constitutes the beginning of the next, statistical analyses of their dependence can be informative about the operating principles of the underlying mechanism. Both these issues are addressed by all three studies included in this thesis.

The main goals of this work are to summarise and amend a body of research pertaining to fundamental properties of human timing, and to propose a preliminary model for the basic mechanism by which time intervals are judged and produced. It would be premature to aspire to a structural model, because neurophysiological research on this level of CNS function is still in its infancy. However, it is argued that behavioural data already suffice for identifying important characteristics of a functional model. Given the wide scope of timing, which encompasses a multitude of scientific disciplines and subdisciplines, it is not feasible to provide an exhaustive review of related research. Rather, selected references from the literature are given on the basis of their relevance for the principal issues under discussion.

Chambers dictionary defines timing as "fixing, choosing, adjusting, ascertaining, or recording of time: co-ordination in time", which implies both experience and behaviour, and a key assumption of the present work is indeed that essential features of human timing in the range of seconds are highly general and build on common design principles. Judging, estimating, and discriminating time

intervals, and behaviours such as producing and synchronising with timed events, are believed to be two sides of the same coin.

William James, in his still highly readable book *The Principles of Psychology* (1890) dedicates an entire chapter to the perception of time, in which he relates some empirical research that demonstrates duration-specificity. This includes limits for which two sensory events become merged into one perceived event, both within and between modalities, and an optimal duration for discrimination in the range from 400 to 750 ms. He contends that our experience of time's flow is discrete, and argues that this is due to the discreteness of our successive acts of recognition or apperception of what it is that we perceive (cf. Brown, 1990). As a neural mechanism to account for the ability to judge and produce time, James suggested that old and faint brain processes overlap with recent and strong ones, and that it is the amount of overlap that determines the feeling of the duration occupied (James, 1890, p. 635). Thus, observations of cross-modal similarities and relatively precise timing abilities exercised at will rendered the notion of a specific timing mechanism as irresistible then as today, more than 100 years later.

Equally irresistible is the conception of this mechanism in terms of a clock, or, more precisely, a clock-counter (Ivry, 1996), a device which measures a long interval by accumulating shorter intervals and keeping track of their number (e.g. Allan, 1992; Eisler, 1975; Eisler, 1981; Eisler & Eisler, 1991; Ivry, Keele, & Diener, 1988; Treisman, 1963; Treisman & Brogan, 1992; Wearden, 1991). A critical property of a clock-counter is the duration of the shorter intervals, or clock ticks, which may have a fixed (Allan, 1992) or variable period (Killeen, 1992), may be serially dependent or independent, and may exhibit different statistical distributions, and so forth. Furthermore, the clock ticks may or may not be equal to the smallest unit of time in the system, in other words the system's temporal resolution. The notion of a "time quantum" was initially suggested by von Baer (1864) and notable investigations in this vein have been made by Geissler (1987), Stroud (1955), and Collyer and colleagues (Collyer, Broadbent, & Church, 1992; 1994).

The clock-counter is challenged by the interval timer, which postulates that different durations are timed by distinct elements, much as hour-glasses containing different amounts of sand. These elements could speculatively be conceived as different neural structures or substructures, such as "taps" in a delay line (e.g. Moore, 1992). According to the parsimony of evolutionary design, such elements should be implemented only for durations of ecological relevance, which furnishes the interval timer concept with a principled reason for the duration-specificity of timing. Another attractive feature of interval timers is that plausible neural implementations can be imagined (for reviews see Ivry, 1996; Miall, 1996), for example as a loop involving the supplementary motor area, the puta-

men, and the ventrolateral thalamus (Rao, Harrington, Haaland, Bobholz, & Cox, 1997) or by varying activation in the Purkinje cells in the cerebellum (Fiala, Grossberg, & Bullock, 1996). Compared with representing a number in the neural system, as implied by clock-counter models, it is also more plausible that interval-based time be represented as a spatial map (Buonomano & Merzenich, 1995).

A third direction in theorising about timing attempts to dispose of specific timing mechanisms altogether, letting the interaction of biomechanical constraints and dynamical coupling between various components of the system determine its temporal characteristics. The problem with this approach is that it does not directly account for timing without action, whereas empirical data indicate significant similarities across perception and action, and also across different kinds of action (Keele, Pokorny, Corcos, & Ivry, 1985). A solution would be to propose that timing in instances where action is not possible is nevertheless guided by implicit action (Todd, 1999), which echoes B. F. Skinner's motor theory of speech (Liberman & Mattingly, 1985). Todd (1996; 1999; Todd, Lee, & O'Boyle, 1999) has argued that the musculoskeletal system is internally represented by a *motor image*, which allows operations with the corresponding synergetic elements even if the musculoskeletal system itself does not move. The activation of this motor image to produce discrete actions or temporal judgements requires of course neural mechanisms. However, the difference from specific timing mechanisms is that time itself becomes an emergent result from an implementation of biological and physical constraints.

Empirical movement research based on the dynamical systems approach, as exemplified by recent studies on juggling (Post, Daffertshofer, & Beek, 2000), bimanual co-ordination (Scheffczyk et al., 2000), or postural sway (Jeka, Oie, Schöner, Dijkstra, & Henson, 1998), has to date not had much to say about classical timing issues, such as the discrimination and production of discrete intervals. The conceptual world of this approach is inhabited by masses, damped springs, phase- and frequency-locking phenomena, coupling of non-linear oscillators, with accompanying mathematical apparatus. Viewing the body and its brain as a self-organising and pattern-forming system (Haken, 1983; Haken, 1996; Tass & Haken, 1996), the goal is to describe movement – and ultimately every aspect of biological functioning – in terms of higher-order variables. While the beauty of dynamical systems theory is its holistic approach, this also means that it might be difficult to partial out certain sub-processes, even if they may in reality also appear in isolation. Most areas of research have some amount of experimental or analytical idiosyncrasies, due to either historical conventions or methodological requirements. It is therefore conceivable that the specific mathematical tools within this tradition has encouraged the study of some real-life phenomena but not others. This may be one reason why this tradition has tended

to focus on limb interaction but not on single limb movements, on continuos and repeated but not on discrete movements, and on externally driven but not on self-paced movements.

Self-paced movement is common within the long and heterogeneous tapping tradition, however. By tapping is typically meant repeated beating of a finger against a table top or some sort of sensor. The most widespread variety is speed tapping, which is used clinically as part of motor performance tests, such as the Vienna or Halstead-Reitan test batteries (Reitan & Wolfson, 1993). The person is asked to tap as fast as possible for a prescribed time, typically 10 seconds, and the number of taps is simply counted. More interesting in the present context is the situation where intervals between the taps are recorded and submitted to analyses of dispersion and autocorrelation. Already, it is becoming clear that tapping is a rather imprecise label, because it says nothing about important psychological aspects of the task, such as moving as fast as possible or making precisely timed movements, and producing self-paced taps or synchronising to external events. Nor does it inform us about the characteristics of the intervals to be timed, which may be shorter or longer, and which may be isochronous or anisochronous, such as the conspicuously different intervals that make up rhythms (e.g. Collier & Wright, 1995; Essens & Povel, 1985; Povel, 1984). Furthermore, these kinds of timing tasks need not necessarily be performed with a finger, but other effectors can also be used, such as the wrist, foot (Keele & Hawkins, 1982; Keele et al., 1985), or mouth (Hibi, 1983). Thus, a more precise term for self-paced tapping is isochronous serial interval production (ISIP) (Madison, 2000).

Of special importance for the modelling of discrete sequential timing is the synchronisation-continuation paradigm (Wing & Kristofferson, 1973), in which ISIP is preceded by isochronous sensorimotor synchronisation (ISMS). In this kind of experiment the participant first synchronises to a sufficient number of external events with isochronous intervals to instil a stable performance, after which the stimuli cease and the participant continues to produce typically 20–50 intervals with approximately the same inter onset interval (IOI) as between the stimuli. Data from this continuation phase lends themselves to analysis by the highly influential Wing-Kristofferson timing model (Vorberg & Wing, 1996; Wing & Kristofferson, 1973), which purports to partition the variance among intervals into a central and a peripheral component. This partitioning is based on the fact that successive production intervals are often negatively first-order correlated, at least for shorter IOIs (Madison, 2000). Assuming that both the central and peripheral processes are random, it can on theoretical grounds be argued that the negative correlation is due to random delays in the execution of the movements, that is, muscle response and afferent neural propagation delays. The model will be described in greater detail in the chapter on serial dependency.

The Wing-Kristofferson model has been extended by several researchers (Vorberg & Hambuch, 1978; Vorberg & Hambuch, 1984; Vos & Ellerman, 1989; Wing, 1977a), and has been used for a number of diverse purposes, such as comparisons of uni- and bimanual performance (Helmuth & Ivry, 1996), analysis of clumsy children's movements (Williams, Woollacott, & Ivry, 1992), and the effects of damage to various neural structures, such as the basal ganglia (Harrington, Haaland, & Hermanowitz, 1998; Wing, Keele, & Margolin, 1984), the cerebellum (Franz, Ivry, & Helmuth, 1996; Inhoff & Rafal, 1990; Ivry et al., 1988), or both (Ivry & Keele, 1989; Middleton & Strick, 1994; Shimoyama, Ninchoji, & Uemura, 1990).

It is common within this tradition of sequence production to distinguish between open-loop and closed-loop models (Ivry & Keele, 1989; Wing, 1977b), concepts which will be discussed in some detail in the modelling chapter. The idea is that any loop providing feedback or rapport with preceding intervals is cut open (hence open-loop) in a mechanism which produces time intervals in splendid isolation, such as might be expected by an oscillator. In contrast, a closed-loop mechanism might be conceived as a delay line which initiates or "resets" itself for a new period once the current interval has run out. However, other important properties are laid open by this distinction, and it is not clear on which temporal level the feedback is supposed to operate; on the level of the smallest time units (when applicable) such as oscillations or "clock ticks", on some level of output from the mechanism, or on the level of timed overt behaviour.

It should also be noted that timing research with general reference to the internal clock concept and its properties is by tradition divided into two branches, exclusively concerned with either discrete intervals or with sequences of intervals. This is unfortunate, because results suggest that they share significant properties, as will be argued in the following chapter.

Duration-specificity

An important question about a system is whether it is scale-invariant. If it works the same way for all parameter values, then it is a truly linear system. Biological systems are, on the contrary, intrinsically dynamical, which means that they behave differently – or not at all – for certain values, and they typically behave well only for values they were designed for by evolutionary selection pressures. Thus, a good hunch about these pressures can help to interpret the goals of a system, and knowledge about the dynamics of the system can help to understand what it was designed to do. This section is concerned with the dynamics related to time itself, that is, to the duration of intervals being processed.

A large part of the timing literature has tacitly ignored duration-specificity because other issues have been in focus, and experiments using sequences of intervals have typically used only one or a few different inter onset intervals (IOI) within the range 250–800 ms. Another large part of the literature has addressed whether Weber's law applies to timing, much of which advocates the *scalar timing theory* (e.g. Wearden, 1999), which is based on clock-counter modelling of timing. According to this framework, the mean time intervals produced should closely match the physical time presented or required, and the standard deviation of the reproduced intervals, or intervals bounded by discrimination thresholds, should increase linearly with the duration of the interval to be timed. The scalar relationship between the variability of timing and the interval to be timed is a critical feature of the scalar timing theory (Church, 1984; Gibbon & Church, 1990; a comprehensive review can be found in Gibbon, Malapani, Dale, & Gallistel, 1997).

However, a number of studies have suggested discontinuities in the function of time close to 1 s for the discrimination of timbre (Kubovy & Howard, 1976), discrete intervals (Grondin, Meilleur-Wells, & Lachance, 1999), the last interval in a series (Halpern & Darwin, 1982), and cyclic temporal displacement (Fraisse, 1967). Other instances of a breakpoint close to 1 s have been found for the magnitude of asynchronies in ISMS (Jingu, 1989; Woodrow, 1932), and the visual representational momentum effect (Freyd & Johnson, 1987). Another breakpoint has been reported close to 1.8 s for the perceptual integration of a sequence of events (Franks & Canic, 1993), for discrimination of discrete intervals (Getty, 1975), and for ISMS, in which case the asynchronies become very large or are replaced by simple reaction times after the stimuli (Mac Dorman, 1962; Mates, Radil, Müller, & Pöppel, 1994; Najenson, Ron, & Behroozi, 1989; Woodrow, 1932).

Already Stevens (1886) noted what he described as fluctuations in his records of successively produced time intervals, and that the relative size of these fluc-

tuations seemed to increase for longer IOIs. Although Stevens did not provide dispersion measures, nor a complete presentation of all his data, subsequent research seems to corroborate his observations. Woodrow (1932) let people attempt to synchronise with an isochronous sound sequence, and found that the coefficient of variation (*CV*) for the deviations between the stimulus sounds and the responses (about the deviation's mean) was substantially larger for 2 s IOI (4.5%) and 4 s IOI (6.1%) than for IOIs between 571 and 1,000 ms (3.4–3.9%). This increase may not seem alarming, but it means that the average deviation was 90 ms for 2 s IOI and 242 ms for 4 s IOI, which is far from perceived isochrony (Madison & Merker, 2000). Thus, one might conclude that all participants failed to synchronise for IOIs from 2 s and up, in terms of how they must subjectively have reached their goal. In a similar study Mates, Radil, Müller and Pöppel (1994) addressed the nature of the synchronisation errors with a somewhat more sophisticated analysis and more closely spaced IOIs: 300, 450, 600, and 900 ms, and 1.2, 1.8, 2.4, 3.6, and 4.8 s. They found that participants, beginning at IOIs from 1.8 to 3.6 s, adopted one of two different strategies for the longer IOIs. One was to anticipate the next stimulus, which led to highly variable deviations in the range of 250 to 300 ms, and the other was to respond as soon as possible after the stimulus, which yielded typical reaction-time values close to 150 ms, with small variability. Also, the mean measured integration interval for sequences of isochronously spaced sounds with different intervals from 200 ms to 1 s was 1.7 s for 13–14 years old listeners (Szelag, Kowalska, Rymarczyk, & Pöppel, 1998).

Given these concordant discontinuities across various temporal tasks, it appears remarkable that timing should adhere to Weber's law, as argued by scalar timing theory. One explanation for this inconsistency might be that few of the overwhelming number of studies in favour of Weber's law have used closely sampled levels of durations across a wide range, which means that possible discontinuities in the function of time might have passed unnoticed. Indeed, out of some 40 studies to my knowledge which support scalar timing, only two had durations that traversed either of the suggested breakpoints, namely 1 s (Wearden & McShane, 1988) and both 1 s and 1.8 s (Allan & Gibbon, 1991). Even so, the levels of duration were in these cases few, and possible discontinuities in the function of time between actually applied durations may easily have been overlooked. For example, Wearden (1991) reviewed three experiments; in the first (Jasselette, Lejeune, & Wearden, 1990), pigeons timed intervals from 10 to 70 s by means of a perching response. Human adults produced, in the second and third experiments, intervals from 500 to 1,300 ms (Wearden & McShane, 1988), or a geometrical series of intervals from 2 s to 32 s. With these ranges of intervals, it is obviously not possible to compare the slopes for intervals shorter than 1 s with those for intervals longer than 1.8 s.

There are also claims for adherence to Weber's law without the reference to scalar timing theory, for the reproduction (Getty, 1976) or discrimination (Grondin, 1993) of discrete intervals, and for dispersion during ISMS (Bartlett & Bartlett, 1959). Again, the levels of duration were essentially too few to reveal possible breakpoints; 300, 450, 600, 750, and 900 ms in the former and 125, 250, 500, 1,000, 2,000, and 4,000 ms in the two latter studies. With somewhat closer levels of IOI, Halpern and Darwin (1982) also claimed that the discrimination of the last interval in a series of three obeys Weber's law, although their data show a clear breakpoint between 1,150 and 1,300 ms (p. 88).

Another problem with discontinuities in the function of time is that averaging across participants may spuriously suggest a single breakpoint when there are in fact several across a wide range, as acknowledged by Wearden (1991). For example, if breakpoints would appear across two rather close regions of the time continuum for individual participants, averaged data might give the impression of a single breakpoint in the middle between these regions. Several individual breakpoints across a range are probably common, because large individual differences seems to be the rule when timing is concerned, as becomes evident when individual records are presented (e.g. Mates et al., 1994; Michon, 1964; Michon, 1977).

In conclusion, much of the arguments in favour of scalar timing and Weber's law for time fades when examined in detail. There may be several reasons why these concepts nevertheless remain very popular. One is of course parsimony, in that it becomes possible to describe the standard deviation across a very wide range of durations with expressions in the form $\sigma = ct^\beta$, where t is time, c is a constant, and the exponent β can be given one single value. Typical β values in the timing literature are 1–1.1 for discrimination of discrete intervals (Ekman & Frankenhaeuser, 1957; Michon, 1967a) (M = 0.9 according to an extensive review by Eisler, 1976) and 1.5 for ISIP (Michon, 1967b). Another reason may be that, although human timing is qualitatively different for different regions of the time continuum, specifically below and above approximately ~2 s (e.g. Getty, 1975; Pöppel, 1996), the human timing characteristics happen to match quantitatively where these regions intersect. Maybe this is in fact no coincidence, but the result of adaptation. Furthermore, when time as a stimulus is sampled geometrically, as is very common in timing studies, this may very well help to create an impression that the timing errors also increase geometrically.

However, if the functional utility of predictive timing is considered, one realises that a more or less constant Weber fraction only has practical relevance for our interaction with the physical world when intervals are relatively short. The value of predicting a future important event, such as being hit by a falling rock, diminishes rapidly as a function of the temporal error. Timing is very precise for shorter intervals, such that for a large number of 500 ms intervals both the pre-

dicted standard deviation (e.g. Michon, 1967b; Truman & Hammond, 1990) and the discrimination threshold (e.g. Halpern & Darwin, 1982) are approximately 25 ms. Only in extremely skilled tasks has such small an error any consequence. For 1.5 s durations, on the other hand, this figure has increased to about 80 ms, but it is still substantially smaller than the simple or one-choice reaction time at around 200 ms (Kauranen & Vanharanta, 1996). Amassed data from a large number of different timing tasks (Gibbon et al., 1997) would indicate that this advantage disappears for intervals of a few seconds (cf. Pöppel, 1996), as the average error becomes larger than the reaction time. From an ecological perspective, then, one can argue that there is no use for precise timing of longer intervals, because simple or even multiple reaction time is a faster and more flexible guide for action. When precision is too poor to allow prediction of events, and hence reasonable synchronisation with the environment (cf. Madison & Merker, 2000), there is essentially no need for precise timing at all. In fact, the only instances where humans are required to make precise timing of intervals longer than ~2 s are in laboratory tasks. Even in our modern mechanised habitat, it appears that intervals for which timing is critical are shorter than 2 s for all other activities, such as music, dance, sports, vehicle driving, and speaking, reading, and writing. The possible significance of scalar timing lies therefore not with the usefulness in terms of environmental demands or adaptation, but with the implementation in the neural system. Indeed, the notion that one single mechanism operates throughout the entire time range is both elegant and parsimonious. However, scalar timing derives its predictions from a clock-counter model, which assumes neural structures that can function (a) as an oscillator, (b) a counter or register, and (c) as a comparator that can handle the entity stored in the counter, the two latter of which are highly implausible (Ivry, 1996).

In view of the lack of timing studies with both a wide range of intervals and close spacing among them, one of the purposes of studies I and II was to examine the existence of possible breakpoints in both production and perception of a series of intervals. Sequences with temporal drift was used in Study II as a corollary to the drift observed in Study I, and as a means to tease out some aspects of temporal sensitivity not previously considered.

Drift in production (Study I)

Study I comprised two classical synchronisation-continuation (i.e. ISMS-ISIP) experiments across the range 700–2,200 ms, with 400 ms also included. The purpose was to detect possible breakpoints in this range, given that such had been found for a variety of other temporal tasks, as have been reviewed above. To this end, the spacing of IOI levels was closer than in previous studies with similarly wide ranges (Gilden, Thornton, & Mallon, 1995; Michon, 1967b; Truman & Hammond, 1990), namely 400–2,200 ms in six equally spaced levels in Experi-

ment 1 and 19 levels in Experiment 2 (50 ms steps for 700–1,200 ms, 100 ms steps for 1,200–1,600 ms, and 200 ms steps for 1,800–2,200 ms IOI. Specifically, Study I proposed that ISIP dispersion might be an amalgam of variability that stem from different sources, and that these may be different functions of the IOI. These sources were drift, that is, local trends in the mean, negative first-order autocorrelation, which is the only directly computable component of the Wing-Kristofferson model, and purely random variability.

Ten women and ten men, 22–36 years old and with a wide range of music training among them, took part in individual sessions lasting 40–60 minutes. A PC administered all experimental conditions in a different randomised order for each participant, and produced the sounds and collected the responses. The participants tapped a sensor plate with a rubber clad surface, and stimuli of approximately 30 ms supra-threshold duration with a clicking quality were presented through headphones. One important difference from previous ISIP studies was that no measures were taken to restrict drift, such as extensive training, de-trending, or omission of non-stationary data series.
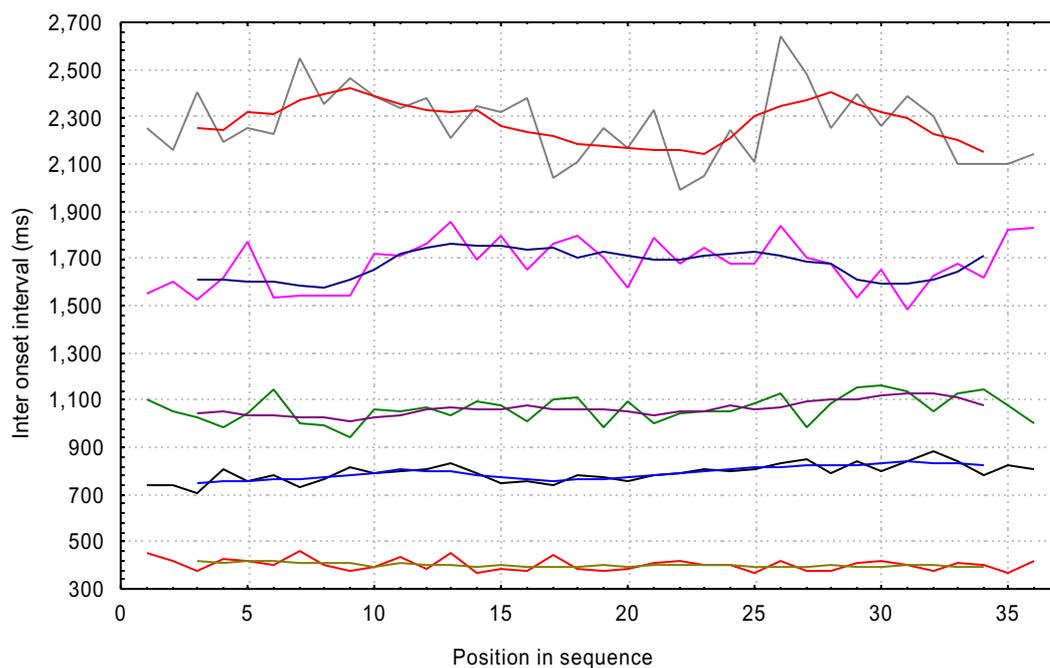

Figure 1. Raw data from one participant in the production (ISIP) phase. The thicker lines are five point moving averages. Reprinted from Madison (2000), Rhythm Perception and Production, pp. 95–113, Lisse: Swets & Zeitlinger. Used with permission.

14

Figure 1 shows five ISIP series for one participant. Five point moving averages are fitted to the raw data, and their smooth waves suggest to the eye that there is drift in the data. The second from the bottom, which is preceded by ISMS to 50 sounds with 700 ms IOI, is also shown in Figure 2. The fitted regression line shows a substantial linear trend across the entire series, and the dotted line shows the same data with this trend subtracted. A five point moving average is fitted to the detrended data, which appears to denote the same relative amount of drift as was seen for the slowest series in Figure 1. The points to be noted about this figure is that there remains a non-linear drift even when the data are detrended, that the trend alone represents a substantial amount of dispersion (15.7 ms SD in this case), and, accordingly, that detrending reduces the dispersion (from 38.7 to 30.1 ms SD).
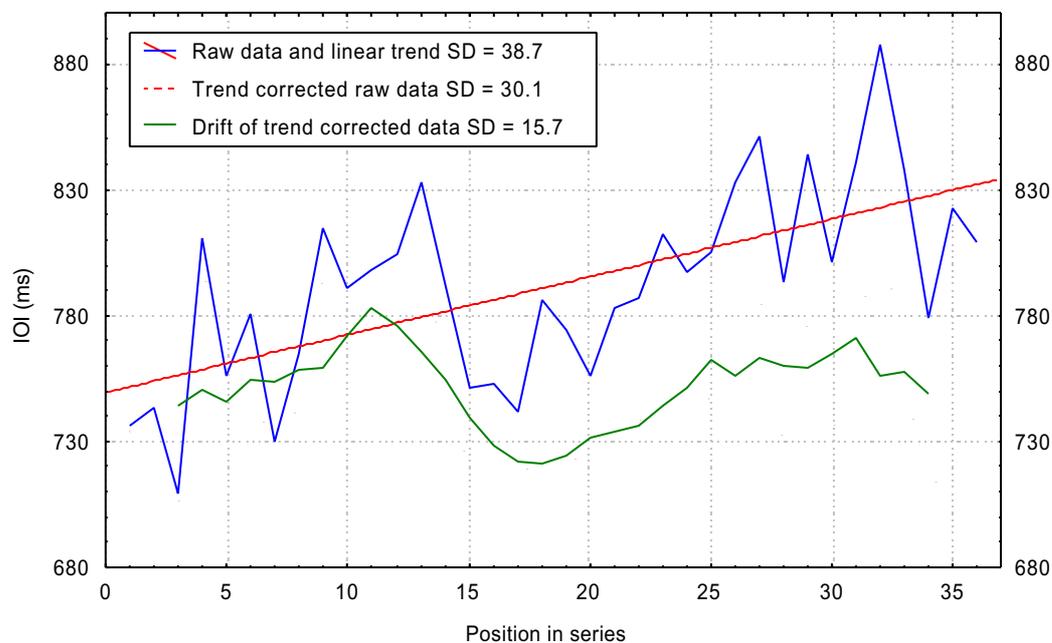

Figure 2. Raw data from one participant in the production (ISIP) phase after synchronising to 700 ms IOIs. The straight line is the linear trend, and the dotted line is the residuals when the trend is subtracted. The thicker line is a five point moving average of the trend corrected data. Reprinted from Madison (2000), Rhythm Perception and Production, pp. 95–113, Lisse: Swets & Zeitlinger. Used with permission.

The first-order autocorrelation (r_1) was negative across the whole range of IOIs for ISMS, and increased in the negative direction for longer IOIs. For ISIP, in contrast, r_1 was negative for shorter IOIs, as predicted by the Wing-Kristofferson model, but became positive for IOIs longer than 950 ms. Break-points in these functions were suggested close to 1,400 ms for ISMS, and some-

where between 1,000 and 1,400 ms for ISIP. There was a substantial correlation (.63–.75) between drift and autocovariance for ISIP in the midrange of IOIs from 700 to 1,800 ms, which suggests that increased drift is responsible for the positive covariance and hence also for part of the dispersion. This is based on the relationship between linear drift and variance

$$SD = f'(w)\sqrt{\frac{N(N+1)}{12}} \quad ,$$

where $f'(w)$ is the drift expressed as the difference in the local mean as a function of the number of intervals N, which might be given by a regression line fitted to a data series with monotonic and linear drift.
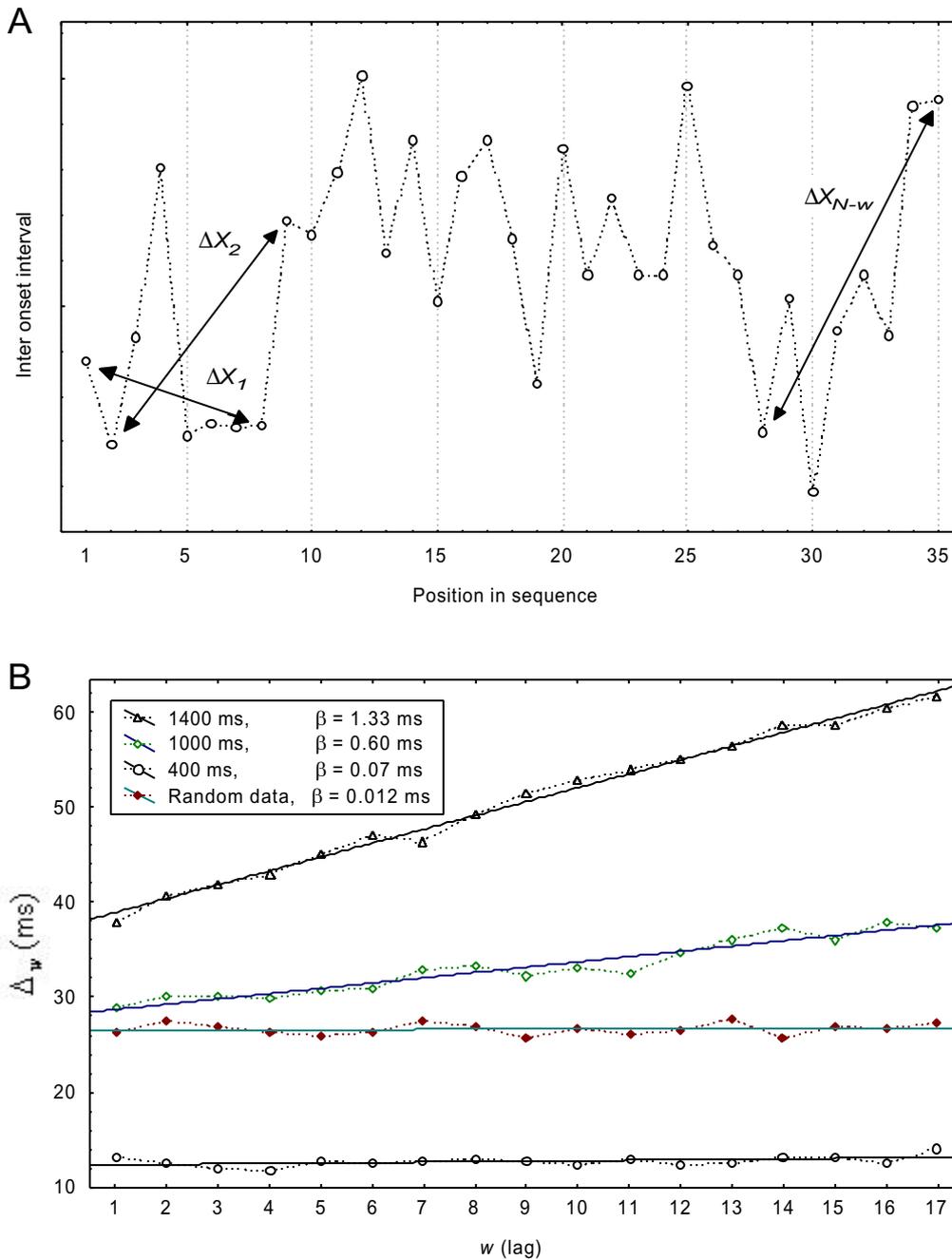
Figure 3. A. Diagram showing how differences were calculated according to $\Delta X_i = |X_i - X_{i+w}|$, in this case for $w = 7$. Note that only the vertical distance is considered.

B. Plots of Δ_w as a function of w for example series with 400, 1,000, and 1,400 ms inter onset interval, and also for a mock series with random data ($SD = 37$ ms). To each plot is fitted least squares regression lines, whose slopes are given in the legend. Reprinted from Madison (2001) with permission from the American Psychological Association.

A measure of drift was devised in Experiment 2, with the purpose of ac-counting not only for linear but also for non-linear drift with arbitrary form of the function. This measure is described in detail in the article. In short, it is the slope of a least-squares simple regression line fitted to a linear-linear plot of Δ_w versus w:

$$f(w) = \Delta_w,$$

where Δ_w is a vector of median differences as a function of the distance or lag w (in number of intervals) in the data series. If $X = X_1, X_2, ..., X_N$ is the observed series of intervals, then, for each index i and lag w,

$$\Delta X_i = |X_i - X_{i+w}|,$$

which is graphically illustrated in Figure 3A. Each point in the vector of differences is given by

$$\Delta_w = \text{med}[\Delta X_1, \Delta X_2, ..., \Delta X_{N-w}].$$

If there is drift in the series, the differences between data points farther apart should on average be greater than between data points close to each other, and Δ_w should increase as w increases, which is exemplified in Figure 3B. For seri-ally independent or stationary processes, on the other hand, $f(w)$ should be zero. An estimate $f'(w)$ for the portion of Δ_w relevant to drift was devised, namely for $4 \leq w \leq N/2$. Hence, the shortest distances are avoided, because the first-order correlation gives rise to larger variability for near-neighbour intervals, and longer distances than half the series (i.e. $w > N/2$) would mean that values in the middle became strongly over-represented. The major point with this method is that $f'(w)$ can encompass non-linear processes, which will be elaborated more on in the following chapter. Assuming for simplicity that the drift is linear, that is, a trend, the standard deviation attributed to it is given by

$$s_d = \begin{cases} f'(w)\sqrt{\dfrac{N(N+1)}{12}} & \text{if } f'(w) \geq 0 \\ 0 & \text{otherwise} \end{cases}. \qquad (1)$$

The purpose of the conditional statement is to filter out a small number of series whose slope was slightly negative, probably due to occasional outliers which in the relatively short series ($N = 37$) had a large effect. The standard deviation attributed to negative first-order dependency was estimated in two ways. The first is represented by the thick line in Figure 4, and was computed from the series which actually had a negative lag 1 correlation, according to

$$s_c = \begin{cases} \sqrt{|Cov_1|} & \text{if } Cov_1 \leq 0 \\ 0 & \text{otherwise} \end{cases}, \qquad (2)$$

in other words ignoring the substantial proportion of series (58%) with a positive r_1. However, the presence of drift, as indicated by (1) and the white area in Figure 4, violates the stationarity assumption (Chatfield, 1980) and should therefore substantially positively bias the autocorrelation. As a consequence, the amount of variability attributed to negative first-order dependency would be underestimated. An alternative, idealised estimate was therefore computed as the mean of the first-order autocovariances of the series with the shortest IOIs (< 900 ms). Under the assumption that this peripheral component is independent of the IOI, as proposed by Wing and Kristofferson (1973), 7.5 ms was used for all IOIs in Figure 4, which is represented by the striped area.
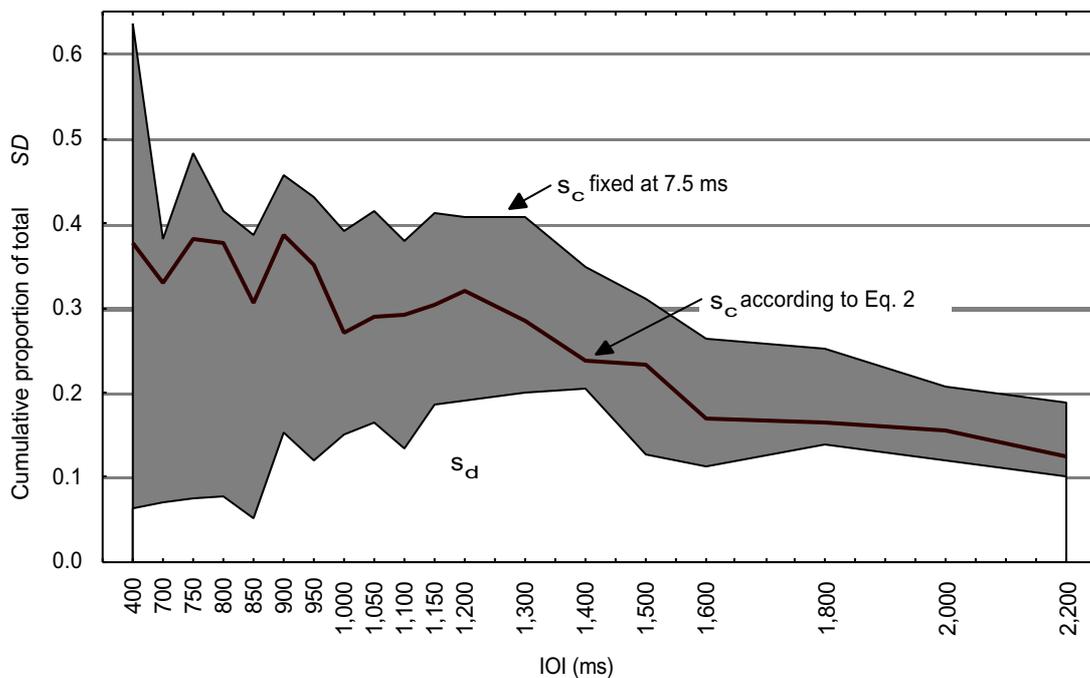

Figure 4. Estimates of the cumulative proportion of total dispersion during ISIP attributable to drift (s_d) and negative first-order autocorrelation (s_c), according to two alternatives: fixed at 7.5 ms and estimated by Equation 2. Note that the distance between 400 ms and the other levels of inter onset interval (IOI) is not proportional. Reprinted from Madison (2001) with permission from the American Psychological Association.

Thus, Study I showed that the overall dispersion across an ISIP series is indeed the sum of dispersion from different processes, and that these contribute differently as a function of the IOI. The relative contribution of drift increased

with the IOI, but seemed to be largest in a midrange from approximately 1 s to 1.4 s, whereas the contribution of first-order dependency was large (~25%) for IOIs shorter than 900 ms, and decreased for longer IOIs. However, at least part of this decrease is attributable to a positive bias due to the non-stationarity imposed by drift. Breakpoints in the respective functions of IOI were indicated by piecewise linear regression close to 1.4 s for SD and r_1, and also close to 1 s for $f'(w)$.

These breakpoints correspond with qualitative changes in performance for other temporal tasks, which suggests common timing processes across modalities and tasks.

Sensitivity for drift in auditory sequences (Study II)

Based on the suggestion that drift is a significant process in the production of time intervals, Study II sought to model how the information in auditory drift sequences is used by the perceptual system, in terms of detection thresholds. The thresholds were estimated by an adaptive psychophysical method known as parameter estimation by sequential testing (PEST) (Gescheider, 1997). The variables were the number of intervals in a sequence (Nint), the IOI between auditory events, and the direction of the drift; increasing or decreasing IOIs. Drift was in these experiments defined as the increase or decrease of each successive interval by a fixed amount of time.

There have been no models proposed for the perception of temporal drift. The simplest idea is that adjacent intervals are compared. It would in this case make no difference how many intervals were present in a sequence, as the comparison is always local. It seems reasonable, on the other hand, that it would be easier to perceive drift in a long sequence of sounds than in a short sequence, and hence that increasing Nint somehow be used to decrease the JND. This could be achieved by a *summation model*, according to which accumulated differences between successive intervals are used, in the simplest case comparing the first and last interval in a sequence. One obvious problem is that, as additional intervals are taken into account, the first and last intervals become separated by a duration which may exceed limits for temporal integration (e.g. Pöppel, 1997). An alternative conception is suggested by the *multiple-look model* (e.g. Drake & Botte, 1993), according to which a perceptual judgement can be based on multiple occurrences of a certain quantity, presumably in a similar fashion as a statistical inference procedure. On the other hand, such an abstraction or integration might not be possible for drift, in which there is strictly speaking no sampling of almost-identical values from which central and dispersion measures may be derived.

Methods

A total of 22 women and 22 men participated in the four experiments in Study II. They were 20–40 years old and had a wide range of music training among them. Each person received all experimental conditions in an individually randomised order within one sessions lasting 30–90 minutes. A custom-designed software running on a PC administered the PEST procedure and all other aspects of the experiment. The stimuli were sequences of identical sound events produced by an *Alesis D4* drum sound module Each stimulus sequence started with the nominal IOI, and every successive IOI was either increased or decreased by a fixed amount of time. After hearing a sequence of sounds the participant was required to indicate whether drift had been detected by pressing one of two keys on the computer keyboard (marked YES or NO). A response was only accepted after all sounds had been issued, so that it was not possible to pre-empt a stimulus. Each response was followed by a 1 s break, after which the next stimulus sequence started with the nominal IOI. A trial was ended when 40 responses had been made, if the criterion was not met earlier.

Results and discussion

Nint was the primary variable in Experiment 1, while both levels of direction were included, and the IOIs were kept to optimal levels at 500 and 600 ms (e.g. Drake & Botte, 1993; Fraisse, 1982). There was a significant effect of individual differences among participants, and no effect of direction, so the just notable difference (JND) could be summarised by the multiple regression (MRA) equation

$$\text{JND} = e^{\wedge}\left(-2.793 + 0.670 \ln \text{IOI} + 1.084 \ln \text{Part} - 1.236 \ln \text{Nint}\right) \quad (3)$$

Each participant's grand mean across all experimental conditions was entered into the MRA as a variable called Part. The purpose was to minimise the amount of explained variance (R^2) lost due to individual differences, thereby increasing the sensitivity for effects of the other variables on R^2. As predicted, the JND was smaller for 500 ms IOI. The last term in (3) means that additional intervals decreased the JND in a negative exponential fashion. This is in agreement with the summation model, but a MRA model with total change as dependent variable did account for substantially less variance than did (3). It should also be noted that the exponentiality implied by (3) led to a significant interaction between Nint and IOI, according to an ANOVA based on untransformed variables, but that this interaction disappeared when IOI and Nint were log transformed.
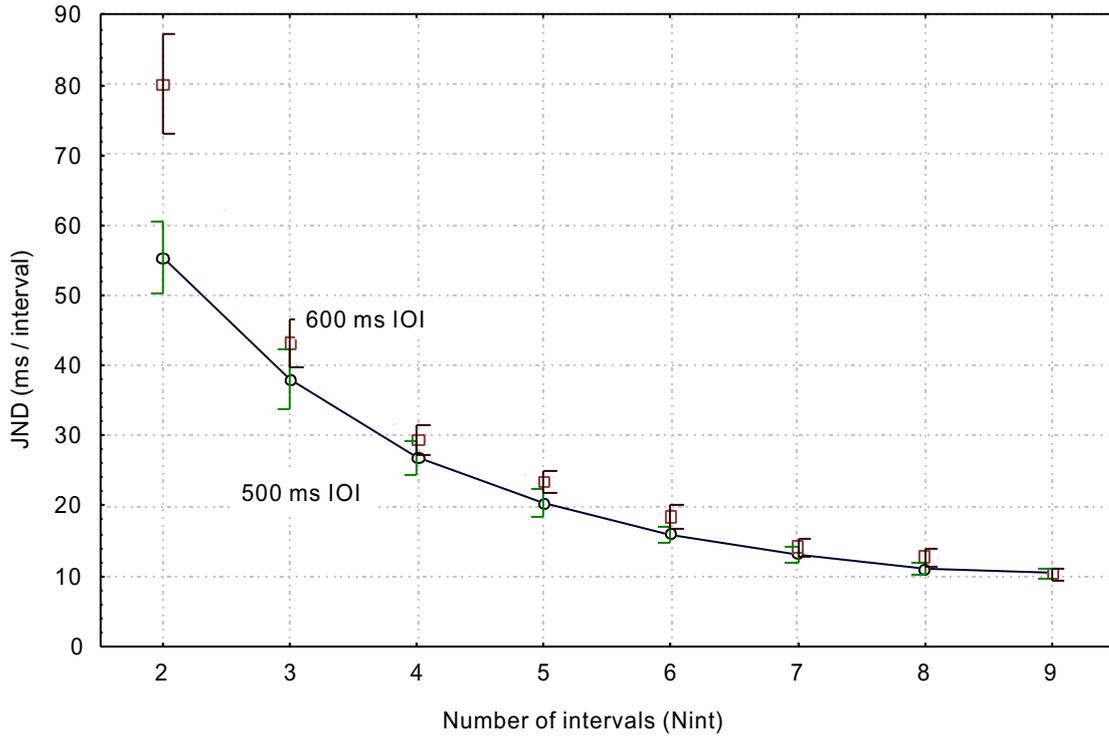
Figure 5. Mean JND for drift as a function of IOI and Nint across direction and participants. Error bars indicate one standard error.

The second experiment addressed whether there was any interaction between Nint and IOI across a wider range of durations, using the coarser levels 3, 5, 7, and 9 Nint, and 500, 800, and 1,100 ms IOI. Systematic combinations of these two variables yielded nominal sequence durations in the range 1.5 s to 9.9 s, which did not traverse the critical values 1 s and 1.4 s. Thus, possible variance due to these discontinuities should only be related to the individual IOIs, not to the sequence durations. The results of Experiment 2 are expressed by (4), in which Nint and participants have almost exactly the same weights as in Experiment 1, but in which the weight for IOI is much larger. This result is consistent with the JND being a non-linear function of the IOI, and that this wider range of IOIs includes at least one such breakpoint at 1 s. In accordance with the additivity of the MRA equation, increased overall weights have to be compensated with a more negative intercept.

$$\text{JND} = e\text{^}\left(-8.824 + 1.522\ln \text{IOI} + 1.168\ \ln \text{Part} - 1.280\ln \text{Nint}\right), R^2 = .699 \quad (4)$$

The most important conclusion from Experiment 2 is that the there was no indication of discontinuity in the JND as a function of the total sequence duration, as would have been expected according to the summation model. This expectation rests on the observation that time and other non-categorisable variables suffers a considerable degradation when they are not contained within a temporal window

of approximately 3 s (for reviews see e.g. Michon, 1978; Pöppel, 1997). The smoothly decreasing JND for longer sequence durations suggests rather that additional Nint be used for detection of drift, in accordance with the multiple-look model.

Experiment 3 was designed to assess the fine-grain effects of IOI on the basis that the effects of IOI did not depend on the number of intervals, as indicated by Experiment 2. The levels of IOI were somewhat less densely sampled than in Study I. One reason was that the drift changes the local IOI so that it eventually will approach adjacent levels of IOI in some trials. Another reason was that the establishment of a perceptual threshold with psychophysical methods is quite demanding, even with an adaptive procedure such as PEST. It was desirable to obtain within-participants data for all conditions, and fewer levels of IOI rendered this task manageable for the participants. There were 13 levels of IOI; every 100 ms from 300 ms to 1,100 ms, and 1,300, 1,500, 1,800, and 2,100 ms. Again, drift occurred in both directions, and was systematically varied with IOI. The results can be summarised by (5), except that the function of IOI was clearly not as smooth as for Nint in Experiment 1.

$$\text{JND} = e^{\wedge}\left(-6.271 + 1.260 \ln \text{IOI} + 0.924 \ln \text{Part}\right) \tag{5}$$

Piecewise linear regression was applied to find possible breakpoints. For the entire range of IOIs, one breakpoint at 28.6 ms JND, corresponding with an IOI between 900 and 1,000 ms, maximised R^2 to 76.0 percent. The remaining range from 1 s to 2.1 s did also suggest a breakpoint, and a straight line did only account for 56.5 percent of the variance. A breakpoint at 46.9 ms JND, which corresponds with an IOI between 1.3 and 1.5 s, increased R^2 to 73.4 percent, whereas another breakpoint in the lower range from 300 ms to 1,000 ms IOI did only marginally increase R^2. In summary, a division of the function in three portions (300–900, 1,000–1,300, and 1,500–2,100) did on average account for 74.7 percent of the variance.
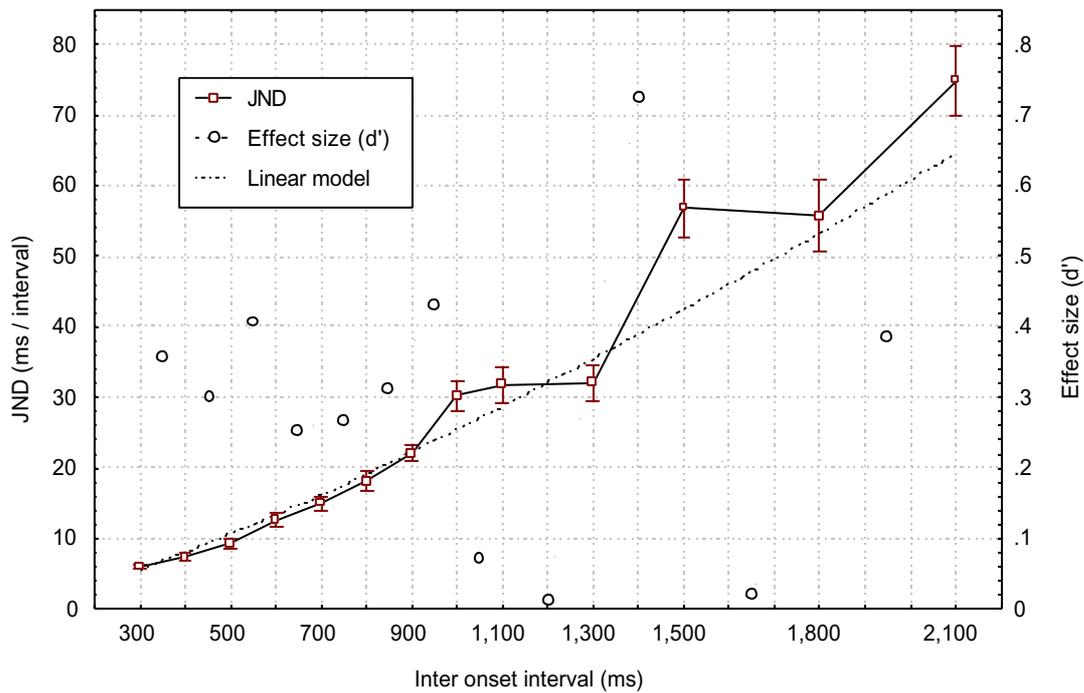
Figure 6. Mean JND as a function of IOI across direction and participants (solid line). Error bars denote one standard error, and the values connected by the broken line show effect sizes for the differences in JND. The dotted line is a plot of the MRA model given by Equation 5.

Effects of subdividing intervals

Another kind of evidence for duration-specificity comes from counting or by other means subdividing intervals, which typically increases the precision in temporal tasks. Getty (1976) found that the standard deviation of reproduced intervals formed by counting at a prescribed rate was smaller than for intervals produced without counting, a result also found for a task requiring short term retention of intervals (Guay & Salmoni, 1988). A similar conclusion was reached by Killeen and Weiss (1987), who analysed temporal discrimination data from several other studies and found that counting within a range of optimal subintervals made the standard deviation independent of the interval to be timed. This is, in other words, scientific evidence for what we all know: that durations from a few seconds up to minutes can be quite accurately timed if we scan "one-thousand-one, one-thousand-two, one-thousand-three" and so forth. This is so self-evident that we hardly reflect why it should be so. Experientially, we lose track of longer intervals, time becomes disjointed and arbitrary, whereas these shorter scanned intervals of approximately 500 ms refer firmly back to the preceding event, which in turn refers to the event before that, and so forth, such that they build a structure comprising the total duration. Counting the number of subinter-

vals is the cognitive trick to overcome imprecision due to uncertainty in this structure, which may work for very large numbers. With the very general ability to count, we relax the need for learning a unique or task-specific structure to organise the subintervals.

However, the above-mentioned studies did not suggest any discontinuities as a function of time, probably due to the range of durations considered. Jingu (1989) let people synchronise either every tap or every third tap with isochronously spaced sounds. He found, in accord with Killeen and Weiss (1987), that the *SD* of the tap intervals was related to their duration rather than the duration between the stimuli. Furthermore, the *SD* demonstrated under both conditions breakpoints close to 1 s and 2 s, indicating that these were also more likely related to the tap intervals. For example, the *SD* was reduced from 900 ms to 300 ms for 3,000 ms IOI, simply by having the participants tap two times between each stimulus (Jingu, 1989). Thaut, Rathbun, and Miller (1997) provided instead one condition with stimuli between the responses in a synchronisation task, in terms of instrumental music, as compared with a non-subdividing metronome signal. The music condition did significantly decrease the *SD*, but only when the inter tap interval was 1,000 ms – not for 200, 250, 333, 500, and 2,000 ms. It is not clear how to interpret that subdivision of 2 s intervals did not also decrease the *SD*, because the authors did not provide any closer description of the musical material. If, for example, the most frequent division of the metronome interval was into two rather than four subintervals, the reduction from 2 s to 1 s did not traverse the critical breakpoint close to 1 s and may therefore not have been sufficient to improve precision.

By dividing the durations 1.2, 2.4, 3.6, and 4.8 s in 0, 1, 2, or 3 subintervals, Grondin (1992) found that counting did only improve the *CV* of discrete interval reproduction when subintervals were shorter than 1.8 s. However, the coarse levels of IOIs did not allow a precise estimation of a possible limit for when subdividing becomes a useful strategy. Psychometric functions from both within- and between-participants designs for interval discrimination indicated such a limit at approximately 1.18 s, based on individual function intersection points across a wide range (Grondin et al., 1999). Some of this individual difference may be attributed to different numbers of subintervals, because, for example, although the instruction in Experiment 4 was to count "fast", this could amount to any number between 3 and 15 for the longer intervals 1.6 and 1.9 s.

Modality and stimulus properties

It is generally found that temporal acuity is greater in relation to the auditory modality, as compared with vision (Bartlett & Bartlett, 1959; Dunlap, 1910; Glenberg, Mann, Altman, Forman, & et al., 1989; Grondin, 1993; Grondin, Meilleur-Wells, Oullette, & Macar, 1998; Grondin & Rousseau, 1991; Kolers &

Brewster, 1985; Kumai & Sugai, 1997; Schab & Crowder, 1989; Wearden, Edwards, Fakhri, & Percival, 1998), touch (Aschersleben & Prinz, 1995), and both vision and touch (Kolers & Brewster, 1985). Some studies which comprise a wide range of durations show a general tendency for smaller differences of modality as IOIs become longer in the range 400–800 ms (Grondin et al., 1998; Kolers & Brewster, 1985), whereas Grondin (1993) found parallel functions for the discrimination threshold across a range of durations from 125 ms to 4 s. The lack of consistency among the studies may be due to differences in both tasks and methods, which are frequently reported to have a significant influence (e.g. Fraisse, 1967).

However, what most notably emerges from these studies are the strong similarities between the modalities, as argued in the next section. A primary question is if a future event can be predicted on the basis of previous events, and the answer is that both vision, touch, and audition allow us to do this with great precision. That is, there is no systematic over- or underestimation of intervals to be discriminated or reproduced. The differences between the modalities is rather the amount of dispersion around the correct mean. A trivial explanation for this can be inferred from the temporal acuity of the senses, namely, that the fusion threshold – the separating interval at which two distinct stimuli become perceived as one event – is about 2 ms for audition and some 40–45 ms for vision (Block, 1990, p. 2; Fraisse, 1984). Synchronisation with tactile stimuli yields intermediate performance as compared with auditory and visual stimuli (Kolers & Brewster, 1985). This difference between audition and vision seems also to be reflected in that simple reaction times are 40 ms longer for visual stimuli (Jaskowski, Jaroszyk, & Hojan-Jezierska, 1990). Thus, the level of sensory input alone yields different amounts of temporal noise, which is likely to account for a large part of the modality differences observed. For example, *SD* as a function of time was 40–50 ms larger for the discrimination of visually presented intervals, as compared with auditory stimuli, across the range 1–4 s (Grondin, 1993).

In contrast, the effect of modality on ISMS variability is much smaller (Bartlett & Bartlett, 1959; Kolers & Brewster, 1985) than for discrimination tasks and for production of discrete intervals, which can be explained by two conclusions based on the results from Study I.

First, I argue that a series of intervals, although attempted to be synchronised with an external signal, are in fact generated internally, but are now and then adjusted to the external signal (cf. Madison, 2000). This view is corroborated by the finding that ISMS data do not fit any simple linear autoregressive or moving average time series model (Mates, 1994b; e.g. Mates, 1994a), but intervals appear to be adjusted after a variable lag, which manifests itself in slow, gradual adjustments to continuously changing stimulus intervals (Hary & Moore, 1985; Hary & Moore, 1987; Kagerer, Ilmberger, Pöppel, Mates, & Radil, 1990). This

behaviour can however be comprised by spectral models (Pressing & Jolley-Rogers, 1997), and fractal models (Chen, Ding, & Kelso, 1997, and unpublished data from Study II). These fractal relationships means that there is long-term serial dependency, which in turn suggests a complex underlying process. Also, responses to a step change in a train of stimulus intervals demonstrate a slow adjustment across a number of intervals (original work in Michon, 1967b; Michon, 1968; Michon & Van der Valk, 1967).

Second, synchronisation yields larger variability among the produced intervals than does production, for optimal intervals up to approximately 700 ms (Study I, Kolers & Brewster, 1985; Rao et al., 1997; Semjen, Schulze, & Vorberg, 2000), which can be interpreted as the "cost" of continually readjusting the internally generated process to the external signal. If each produced interval was simply first-order corrected on the basis of the preceding asynchrony or response interval, this should not lead to larger variability among the produced intervals, given that all other parameters, such as the motor delay, are the same as for ISIP. Thus, the view that IOIs produced during ISMS are internally generated could explain both the dynamics of ISMS and the observation that the variance is not directly related to the temporal noise in the sensory system by which the external signal is mediated.

Another persistent issue is the difference between "empty" time, an interval delimited by two brief sensory events, and time filled with a continuous sensory stimulation other than that before and after the interval. It is well established that the difference between empty and filled intervals depends on the duration to be discriminated (Schab & Crowder, 1989). For auditory presentation, Grondin, Meilleur-Wells, Oullette, and Macar (1998) found that empty 400 ms intervals were more accurately discriminated than filled intervals, but that there was no such difference for 800 ms intervals. For 3 of the 4 participants in Grondin (1993, Experiment 5) empty intervals yielded lower thresholds for 250 ms and 500 ms, but not for 1 s, 2 s, and 4 s, whereas the results for 125 ms were inconclusive. Finally, Triplett (1931), with a large amount of data on the discrimination of 1.5 s intervals, did not find any effect of them being filled or empty.

All in all, and in agreement with Michon (1985), these results indicate that the judgement of shorter intervals may to some extent be influenced by their physical characteristics and the modality by which they are perceived, in contrast to longer intervals. A popular notion is accordingly that shorter durations are perceptually processed, whereas longer durations are cognitively processed, presumably on a higher level in the CNS (e.g. Michon, 1985; Michon, 2000; Rammsayer & Lima, 1991). However, an equally possible interpretation is that longer intervals are subject to additional processes than are shorter intervals, in which case the "perceptual" effects of stimulus properties become obscured by the much lesser precision related to longer intervals.

Conclusions

The reviewed literature and the results obtained in Studies I and II argue quite convincingly for similar properties in the processing of time by the human brain across different tasks and sensory modalities, and that these properties include non-linearity with respect to the duration of the intervals processed. As mentioned before, this should not come as a surprise, because biological systems are typically dynamical, in part as a result of evolutionary adaptation to selection pressures. One can speculate that the ultimate determinants of this adaptation are gravity, mass, and size, inasmuch as the natural frequencies of an organism's body and limbs depend on their respective masses and its physical distribution. These three factors specify the inertia of significant objects in the environment, and hence their time constants. For example, the stride periodicities for a range of larger mammals – from dogs to horses – are within a range from 286 to 1,000 ms; the fastest gait for rats and mice equals 210 and 150 ms, respectively, and all modes of human locomotion are confined to the range 330–1,000 ms (Heglund, Taylor, & McMahon, 1974). It is therefore highly suggestive that, in addition to the breakpoints discussed so far, another breakpoint close to 330 ms is repeatedly mentioned in the timing literature (Collyer et al., 1994; Friberg & Sundberg, 1995; Garner & Gottwald, 1968; Hibi, 1983; Kohno, 1992; Kohno, 1993; Michon, 1964; Peters, 1989).

Further indications about the relation between duration-specificity and environmental factors can be found for spontaneous and preferred tempo (A now relatively dated review can be found in Fraisse, 1982). Spontaneous tempo (also called personal or mental tempo) is what people produce when asked to perform a repeated movement at the most pleasing rate. It is intra-individually consistent (e.g. Harrel, 1937), lies most commonly within the range 400–800 ms IOI, varies greatly among individuals, but does never exceed 1,400 ms IOI (e.g. Fraisse, Pichot, & Clirirouin, 1949). It appears to have a hereditary component, because the differences between homozygotic twins are similar to those between replications given by the same individual, whereas the differences between heterozygotic twins are similar to those found between unrelated individuals (Frischeisen-Köhler, 1933; Lehtovaara, Saarinen, & Järvinen, 1966; Meshkova, 1994). Preferred tempo is the perceptual counterpart to spontaneous tempo, in terms of ratings of goodness across a wide range of tempi, which for more than half of a group of participants corresponded with 500–700 ms IOIs (Wallin, 1911). A modest correlation (.40) between these two measures has been reported (Mishima, 1965), but preferred tempo seems to be most strongly correlated with anthropometric measures determining the torsional motion of the upper body (Todd & Cousins, 1999).

Other arguments for the generality of these findings may be sought from real-world behaviours, such as music and speech, and to some extent from studies of other species.

In music, tempo most often refers to an intermediate and typically isochronous timescale called pulse or beat. I will here let beat designate physical tempo, that is, the intervals determined by a musical score in combination with either a tempo marking in the score or with a real performance, and reserve pulse for the subjective segmentation of time (Madison & Merker, 2000), which often but not always equals the beat. The beat intervals are typically longer than the intervals between the musical events, at the same time as they are shorter than other organisational devices on other temporal levels in the music, such as measures, motifs, phrases, and movements. Musicians' intuitions concur with more psychologically oriented perspectives in regarding the pulse – and hence the tempo – as the most fundamental organising force in music. It is therefore notable that a standard metronome can typically be set within a range from 240 to 44 beats per minute, which corresponds with 250–1,500 ms IOI. The extreme tempi are seldom used, but when they are, short intervals are typically multiplied and long intervals are subdivided to form more perceptually optimal pulse intervals (Handel & Lawson, 1983; Handel & Oshinsky, 1981; Madsen, Duke, & Geringer, 1986). If we consider the IOIs for individual tones rather than the pulse grouping them, similar values are again found. The range of tone IOIs (the grand median across melodies and listeners) for which eight well-known melodies could be identified was 160–1280 ms (Warren, Gardner, Brubaker, & Bashford Jr, 1991).

The situation is a bit different in speech, probably because speech units are shorter than musical sounds, the latter of which can be "carried" by several pulse events. The duration of a single word in normal conversation is typically 400 ms (Warren, 1993), but the limiting factor in speech is rather the duration of phrases. Converging data show that the most common "action unit" durations in spontaneous speech are 0.5–1.5 s, which with the inclusion of more rare instances of durations up to several seconds leads to a median phrase duration close to 2 s (Kien & Kemp, 1994; Vollrath, Kazenwadel, & Krüger, 1992).

It is not straight-forward how to regard language in this respect, being an overlearned skill whose units may be identified with their verbal labels and thus possibly encoded differently than novel or non-speech events (Warren, Bashford Jr, & Gardner, 1990). Experiments with strict control of this factor are pending (but see Kubovy & Howard, 1976). However, studies of auditory pattern discrimination in monkeys (Dewson III & Cowey, 1969) and dolphins (Thompson, 1976, quoted from Warren, 1993) demonstrate a sudden breakdown in performance for patterns which exceed 2 or 3 seconds duration. Finally, a simple eye-

blink response (in rabbits) is possible to condition to a range of intervals up to approximately 1 s, but not above that (Steinmetz, 1990).

Serial dependency

Many natural phenomena demonstrate spatial and temporal dependency. Recent theoretical and analytical developments seem to suggest that this is more or less a natural law (Bak, 1997; Eke et al., 1999; Mandelbrot, 1983; Niklas, 1994; Weigend & Gershenfeld, 1994). This ubiquitous dependency is typically not linear or periodical, but is characterised by a fractal relation between different levels of resolution of the data, a property also called self-affinity (Beran, 1994; Mandelbrot, 1983). For variables measured over time, this translates to data being statistically similar across different timescales. A fractal signal can in the frequency domain be defined as a noise in which all possible frequencies in the relevant range occur simultaneously, but whose relative power is determined by a straight line across the spectrum. So long as the line remains straight, its slope is allowed to vary, which determines the nature of the dependency between the timescales. The noise is independent (i.e. white noise) when the spectrum is flat (i.e. a horizontal line).

The most common type of noise signature in natural phenomena is the so-called $1/f$ noise, with a power density inversely proportional to the frequency ($\sim f^{-1}$), which is usually taken to mean somewhere between f^0 (white noise) and f^{-2} (Brownian motion). For example, $1/f$ noise-type temporal dependencies occur in heart rate (Chaffin, Goldberg, & Reed, 1991), river water discharge (Hurst, 1951; Mandelbrot & Wallis, 1968), air temperature (Jones & Briffa, 1992), rainfall (Sevcik, 1998), geophysics (Mandelbrot, 1967; Mandelbrot & Wallis, 1969), influenza epidemics (Dávila, 1995), and judgements made by human observers (Gilden, 1997; 2001; Pearson, 1902). Processes with a negative slope are also characterised as long-memory processes. It is thus not unreasonable to anticipate $1/f$ noise in other processes with biological origin, such as human timing.

Drift, stationarity, and autocorrelation estimates

The mean, standard deviation, autocorrelation, and other measures based on random Gaussian statistics are frequently calculated for series of produced intervals. These techniques rely on the assumption that samples are independent, which is not the case in the presence of drift or $1/f$ noise. For random variables, larger or smaller samples should make no difference for central and dispersion measures, except to alter the confidence intervals, and neither should there be any significant differences between samples. In the case of variables measured over time, stationarity in the mean, that is, for data $X_1, ..., X_n, E[X_i] = \mu, \ i = 1, ..., n$, is a requisite for avoiding bias in estimates based on time series techniques.

Autocorrelation (or covariance), moving average models, and autoregressive models (e.g. Chatfield, 1980) are based on superpositioning two sets of the same data, offset by a certain lag, and calculating the covariance between them. These linear techniques are suitable for detecting periodical variations embedded in random noise. Drift in the mean, which was found and quantified in Study I, constitutes non-stationarity, and results in a positive serial dependency, because successive data points tend to "go together". In the simplest case of a linear, monotonic trend, all data points will be correlated with each other for all lags. Being pursued throughout the entire series, this dependency will be very strong, and will give rise to a positive correlation coefficient that will in many cases overshadow possible periodic variation. Such situations have been simulated by Vorberg and Wing (1996). Even a very small linear trend can severely bias auto-correlation estimates, especially when series are long. In the absence of other variability, a linear trend will, for any lag k, give the autocorrelation coefficient $r_k = 1$, because the autocovariance Cov_k equals Cov_0.

The effect of other kinds of drift is more difficult to predict, and may for the more complex types be impossible to compute (cf. Ogden & Collier, 1999). However, one can intuitively appreciate that a quadratic function will render positive correlations for all lags up to half the period of the function. More generally, a function of any form and with a period close to the size of the data series will contribute to positive correlations. Irregular functions, as those plotted in Figures 1 and 2, will basically yield positive correlations for lags that are smaller than the period of the dominant fluctuations. $1/f$ characteristics, in terms of noise with lower frequencies having larger amplitudes, leads to a complex interaction between the lagged copies of the data series, in which case one can speak of a probabilistic relation between drift and positive lower-order correlations, as some of the fluctuations cancel each other out. A consequence of this is that the standard procedure for detecting non-stationarity, inspection of the autocorrelation function, may not be reliable, since this function would decrease quite rapidly due to more prominent cancellation for higher lags. Another consequence of $1/f$ noise is that longer data series contain longer and hence stronger fluctuations, which makes the positive bias more severe.

It should be emphasised that the sensitivity for drift is a feature of time series methods, and has nothing to do with the processes studied with these methods. It is thus important to distinguish between the time series, and what properties that can be estimated about that, and the properties of the process from which the time series is sampled. Thus, $1/f$ noise constitutes non-stationarity and a substantial bias for traditional time series methods, but it does also stand a considerable risk of going undetected by the same methods.

Fractal time series and the Hurst exponent

As mentioned before, the low-frequency power of $1/f$ noise is stronger than its high-frequency power, in contrast to white noise whose spectrum is flat. More specifically, the spectral power density function $|A|^2 \approx f^{-1}$ for the entire frequency range. The *scaling exponent β*, which is close to –1 for these so-called red or pink noises, can of course assume any real value. For example, $\beta = 0$ for white noise and $\beta \approx 1$ for blue or azure noises, whose high-frequency power is the stronger. Data which produce a non-integer scaling exponent

$$|A|^2 \propto f^{-\beta}, \; -1 < \beta < 0 \text{ or } 0 < \beta < 1,$$

are characterised as *fractal time series* or *fractional Gaussian noise* (fGn) (see e.g. Caccia, Percival, Cannon, Raymond, & Bassingthwaighte, 1997). This linear relationship distinguishes fractal time series from time series with any other form of the power spectrum, and makes it possible to characterise them by a single number denoting the slope of the line.

The foregoing discussion has focused on the frequency domain as an intuitive approach to fGn. More generally, fGn can be conceptualised in terms of the Euclidean dimension (D), which is 1 for a line and 2 for a plane. A plot that fills the plane ($D \Rightarrow 2$) can be said to be more complex than a straight line ($D \Rightarrow 1$). At the same time, adjacent or near-neighbour data points must necessarily be negatively correlated to fill the plane, whereas in a line each point is positively correlated with every other. These relationships are succinctly expressed by the *Hurst exponent* (H). H can assume any value between 0 and 1, and is related to dimension by $H = 2 - D$. The points in a time series are uncorrelated when $H = 0.5$. The relationship with the scaling exponent β for coloured noises is

$$H = \frac{\beta + 1}{2}.$$

Time series with $0 < H < 0.5$, corresponding with azure noises, are negatively correlated and therefore called anti-persistent. Likewise, positively correlated series with pink noise and $0.5 < H < 1$ are called persistent. Formally, the correlation function for lags k of an exact fractional time series can be defined as

$$r_k = \frac{1}{2} \left\{ |k+1|^{2H} - 2|k|^{2H} + |k-1|^{2H} \right\}.$$

The fractal dimension is a theoretical concept derived from geometry, whereas β is an empirical estimate. H was originally also an empirical estimate (Hurst, 1951), but was later formally defined by Mandelbrot and van Ness

(1968). There are unfortunately many inconsistencies in the literature on these issues, and terms can have different meanings in different papers, which is in part due to historical reasons. For example, concepts which essentially describe the same conformity to a law have been developed in parallel in different scientific disciplines, and an agreement on which to use on recently discovered common grounds has not yet been made. Comprehensive discussions can be found in Barnsley, Devaney, Mandelbrot, Peitgen, Saupe, and Voss (1988), Hastings and Sugihara (1993), Mandelbrot (1983), Beran (1994), and Raymond and Bassingthwaighte (1999).

One particularly persistent confusion is that between fGn and *fractional Brownian motion* (fBm), which is by many writers thought to be the same thing. However, the distinction between the two will be of significance in the following discussions. Brownian motion – also called random walk – refers to the trace of small particles in a solution under the influence of random impulses. Einstein (1905) discovered that the distance R covered by a random particle undergoing random collisions from all sides is directly related to the square root of time, thus $R = c\sqrt{t}$, where c is some constant. Although Brownian motion is non-stationary and seemingly deterministic in appearance, it is simply the sum of random increments, and hence *de facto* purely random. fBm is the serially dependent variety of Brownian motion, in analogy with fractional noises, but with the difference that the power spectrum of fBm has a slope β $(f^{-\beta})$ which is 2 greater than that for fGn, which means that

$$
\begin{array}{cc}
\text{fGn} & \text{fBm} \\
-1 < \beta < 1 & 1 < \beta < 3 \\
H = \dfrac{\beta + 1}{2} & H = \dfrac{\beta - 1}{2}
\end{array} \qquad (6)
$$

and H will thus have the same value for fGn's and fBm's related by differencing:

$$ Y_i = X_i - X_{i+1}, $$

where Y is the fGn and X is the fBm.

Methods for estimating the fractal dimension

The most important considerations for choosing among methods for estimating the fractal dimension, be it in terms of β, D, or H, are bias, reliability, and data requirements. Bias refers to the difference between estimated and true H, which is quite large for *rescaled range analysis* (Caccia et al., 1997), *correlation* methods (Schepers, van Beek, & Bassingthwaighte, 1992) and for so-called *dividers* or *box-counting* methods (Hastings & Sugihara, 1993). The latter three types of methods require on the other hand few data points and little computing power.

Spectral analysis methods compute the sine and cosine coefficients for each period $m = 2$–$N / 2$ and attempts to fit a linear regression line to the resulting spectral power density function. Extreme outliers due to "side lobe"-effects and quantising noise make it sensitive for non-sinusoidal fluctuations, and it requires therefore long data series to yield reliable estimates. The bias for spectral methods is a matter of some debate, as they have performed very well for fGn's synthesised with the inverse Fourier transform (Schepers et al., 1992), whose autocorrelation function is different from what is theoretically predicted for fGn. Synthesised data with the correct correlation function (Bassingthwaighte & Beyer, 1991) has on the other hand suggested some problems with spectral methods (Raymond & Bassingthwaighte, 1999).

Dispersional methods are considered to be very robust to various problems with the data, including outliers, they are moderately biased, and require moderate amounts of data (e.g. Bassingthwaighte & Raymond, 1995; Caccia et al., 1997; Cannon, Percival, Caccia, Raymond, & Bassingthwaighte, 1997; Raymond & Bassingthwaighte, 1999). This approach is based on comparing the dispersion for different resolutions of the same data, which closely corresponds with the concept of self-affinity.

Relative dispersion analysis

This method yields H and is also described in Study III. It is based on the change in relative dispersion ($RD =$ e.g. SD / M) as geometrically increasing bins of successive data points are averaged. The RD is under these circumstances reduced by $1/m^{0.5}$ for uncorrelated pink noise, and by $1/m^{H-1}$ for fractal noise, where m is bin size.

First the RD across the entire series is computed. Each pair of data is then averaged in bins, $Y_1 = X_1 + X_2$, $Y_2 = X_3 + X_4, \ldots, Y_{N/2} = X_{N-1} + X_N$, the RD is computed again, and this procedure is iterated for bin sizes 4, 8, 16, . . until they reach a certain fraction of N. The relation between different bin sizes is expressed by

$$RD_m = RD_{m_0} \left(\frac{m}{m_0} \right)^{H-1}, \tag{7}$$

where m_0 is a reference bin size, and H is obtained by fitting a least-squares regression line to the log-log transformation

$$\log(RD)_m = \log(RD_{m_0}) + (H-1)\log\left(\frac{m}{m_0} \right). \tag{8}$$

35

The measure of the fit to the theoretically expected process can be described as the proportion explained variance (S_{pe}) accounted for by the regression line, that is

$$S_{pe} = \left(\frac{N\left(\sum XY\right) - \left(\sum X\right)\left(\sum Y\right)}{\sqrt{\left(N\left(\sum X^2\right) - \left(\sum X\right)^2\right)\left(N\left(\sum Y^2\right) - \left(\sum Y\right)^2\right)}} \right)^2. \tag{9}$$

These measures are exemplified in Figure 7, which plots log RD versus log m, and the S_{pe} for each line fit is given in the corresponding panel. The data are randomly chosen from Study III. None of the plots in Figure 7 are random ($H \approx 0.5$), and explained variances between 97 and 100 percent show that the data generally fit the fractal scaling model very well.
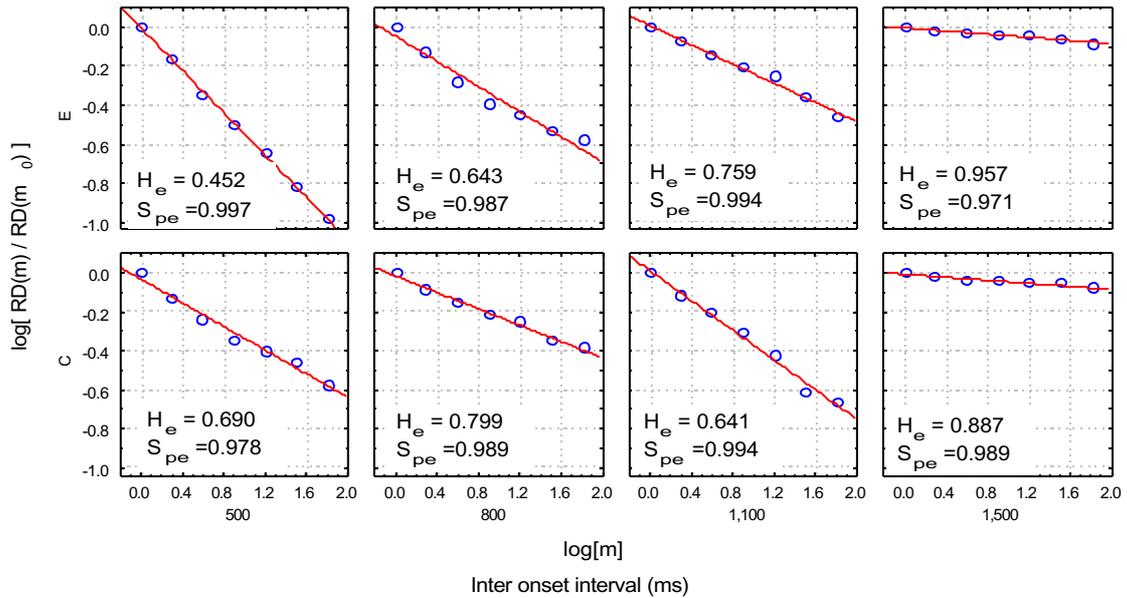
Figure 7. Examples of the estimation of *H* for 8 data series with 256 intervals. Each point is the log *RD* for the corresponding log *m* on the abscissa, and the lines are fitted least-squares simple regressions. The value of *H* corresponding with the respective slope is given together with the S_{pe} at the bottom of each panel.

Serial dependency in timing as suggested by previous research

As early as 1886, Stevens observed in plots of successive ISIP intervals "the constant zig-zag of individual records" and "more or less distinctly still larger and more primary waves" (p. 401). These descriptions conform with negative

first-order autocorrelation, which has already been discussed in Study I, and $1/f$ noise. Stevens' prime interest was not the nature of the variability *per se*, but whether the IOIs tended to drift in one or the other direction. The idea was that there exists a so-called indifference interval, towards which faster and slower tapping rates would eventually drift (e.g. Nicholson, 1925; Woodrow, 1932). One notion about such an interval is that it might constitute the "natural" frequency of some biological oscillator (Vos, van Assen, & Franek, 1997).

An indifference interval would be a simple explanation of drift, but there seems to be no reason that it should imply $1/f$ noise. Since the purpose of this drift would be to arrive at a different mean IOI, it should rather be linear, inasmuch as it could be measured by linear regression across entire data series. However, this seems not to be the case. Linear detrending, for example, does typically have negligible effects (Helmuth & Ivry, 1996; Hulstijn, Summers, van Lieshout, Peters, & van Lieshout, 1992; Ivry & Keele, 1989; Ivry et al., 1988; Kolers & Brewster, 1985).

Fraisse and Voillaume (1971) devised an experiment in which participants were asked to synchronise with sounds that were unbeknownst to them produced by their own taps. Regardless of the IOI (400, 800, 1,600, and 3,200 ms) participants tended to speed up their tapping rate. This tendency was substantially smaller in a condition in which the nature of the feedback was disclosed, but it did not change direction even for the shortest 400 ms IOI. Study I, on the other hand, did not show increasing or decreasing IOIs to be more common than expected by chance for any IOI from 400 to 2,200 ms IOI, except that the shortest 400 ms IOI tended to decrease further.

In a study of the direction of the bias for reproduction of discrete intervals, Woodrow (1934) stated that "it is an astonishing fact that seldom, if ever, have any two of the many investigators who have sought to determine the length of the temporal indifference interval reached the same conclusion." (p. 167). The present empirical status of the indifference interval has not been much improved, as reviewed in Study II. There is still no consistent evidence for effects of direction on the detection of drift, nor for the presence of linear drift in ISIP data.

Regardless of the kind of drift or serial dependency, it increases dispersion. Michon (1966) recognised that drift in ISIP data is a source of error when the *SD* is used as an indicator of perceptual motor load, and applied up to seventh-order polynomials to detrend 200 point ISIP data (1967b). However, later work has largely ignored the serial dependency and its implications. This is conceivably related to the application of time series methods to ISIP data, and their sensitivity for drift. Especially non-linear drift would be impossible to remove correctly, unless the underlying process was known. Thus, both the drift itself and the re-

siduals after possible detrending lead to serious concerns for the bias of autocorrelation estimates (Kolers & Brewster, 1985).

Following McGill's (1962) seminal work, Michon (1967b) and Voillaume (1971) subjected their data to autocorrelation analysis. But it was not until Wing and Kristofferson (1973) published their decomposition equation

$$
\begin{aligned}
s_M^2 &= -Cov(1) \\
s_C^2 &= Cov(0) + 2Cov(1)
\end{aligned}
\tag{10}
$$

(where M and C denote the peripheral and central components, respectively) that the application of autocorrelation came into widespread use. Equation 10 looks more complex than it is, which has to do with the lag 1 correlation being negative. The first expression is based on the fact that a negative covariance contributes equally to the dispersion as does a positive covariance. The second expression means that the central variance is the difference between total variance (lag 0) and variance attributed to negative lag 1 correlation (the first expression), hence more intuitively

$$
s_C^2 = s_{total}^2 - (-Cov(1))
$$

or simply

$$
s_C^2 = s_{total}^2 - s_M^2 .
$$

This means that, given that s_M^2 is unbiased, s_C^2 is a dustbin variable that may include any unknown processes. Regarding the bias, it is notable that Wing and Kristofferson did only use trained participants, short intervals (180–400 ms), and short series (30 intervals). The foregoing review of the literature indicates that non-stationarity would have violated the model, had they not taken these measures to restrict the drift. In the years to follow, studies which applied the model provided a sample-card of means to obtain stationarity. In addition to using trained participants and limiting IOIs and series length, participants and data have been screened (Vorberg & Hambuch, 1978), participants have been pre-trained with feedback, and various kinds of detrending has been applied (e.g. Keele et al., 1985; Kolers & Brewster, 1985; Michon, 1967; Wing, Church et al., 1989). In spite of this range of devices available, several authors have noted problems with the model (Ivry & Hazeltine, 1995; Ivry & Keele, 1989; Study I and Madison, 2000; O'Boyle, Freeman, & Cody, 1996).

Relatively long-term fluctuations in the mean IOI have also been reported in the context of bimanual production of polymeters (Engbert et al., 1997; Krampe,

Kliegl, Mayr, Engbert, & Vorberg, 2000), but they were not the focus of interest and were not analysed *per se*.

The most explicit claim to date for structure in ISIP data was made by Gilden, Thornton, and Mallon (1995) who let six participants without particular training or timing skills produce 1,000 intervals for each of six IOIs in the range 0.3–10 s. The spectra were $1/f$ for all frequencies less than ~0.2 Hz, but they had also a quadratic trend for higher frequencies. This trend became more pronounced for shorter IOIs, and was attributed to the negative first-order correlation demonstrated in numerous studies.

Yamada and associates did also find an approximately inverse relation between frequency and power spectra (Yamada, 1996; Yamada & Tsumura, 1998). In contrast to Gilden et al., these authors argued that the power spectrum exhibits a minimum for a period corresponding to 20 events, regardless of the IOI. However, the shape of the low-frequency portion of the spectrum should be interpreted with caution since the length of the analysed data was only 200 points.

Gilden (1997) applied spectral analysis to the fluctuations in reaction time for mental rotation, lexical decision, and serial and parallel visual search. He found that a substantial proportion of the variance among successive deviations from reaction time means could be characterised as $1/f$.

$1/f$ noise has also been found in the asynchronies during ISMS (Pressing & Jolley-Rogers, 1997), a finding that Pressing (1999) employs as one building-block of a formal theory of referential control in both cognition and action. A discrete control equation, central to this theory, is proposed to bridge the gap between non-linear dynamical motor phenomena and linear random timing models, such as clock-counters and interval timers. However, neither the empirical evidence nor the mathematical modelling go beyond sensorimotor synchronisation, and it remains therefore quite obscure if this theory is applicable to ISIP.

Fractal dimension of ISIP (Study III)

Converging evidence indicates that human serial timing may have a fractal structure. Given that it may also be a compound of several processes, as suggested for example by the conclusions of Study I and of Gilden at al. (1995), a robust but yet theoretically well founded method for the estimation of the fractal dimension was desirable. The previously described *Relative dispersion* is such a method, which has also the advantage of having been carefully evaluated (e.g. Caccia et al., 1997). That this method happens to yield H is the main reason why H rather than β or D was the dependent variable in Study III.

The reviewed research, including Study I and II, has suggested qualitative differences for regions of the time continuum divided by breakpoints close to 1 s and 1.3–1.4 s. Study I indicated leapwise increasing relative amounts of drift for

these durations, a pattern whose perceptual counterpart was echoed in Study II. Thus, apart from the assumption that ISIP variability can indeed be modelled as fGn, there is also the possibility that H would increase with the base interval across the range 500 ms to 1,500 ms. That would also be one possible account of increasing relative drift, since larger H means that slower fluctuations have greater relative amplitude. It could also be that independent slow or even linear drift is added for longer IOIs, or that the relative amount of purely random variability decreases. These possibilities have to be taken into account when the conformity of ISIP data with fGn is tested. Large individual differences have frequently been reported for timing tasks, as mentioned before, which is another important issue. Specifically, one should consider the following concerns.

First, there may be individual differences, either due to hereditary components (e.g. Meshkova, 1994), music training (Franek, Mates, Radil, Beck, & Pöppel, 1991), or experimental training (Nagasaki, 1990). However, music training has generally been found to affect simple, straightforward timing tasks very little, or not at all, whereas it seems to matter more for specialised skills, such as complex movements (e.g. Yamada & Tsumura, 1998). Even with large group differences in training, such as concert pianists versus lay people, individual differences remain larger within groups than between groups (Keele et al., 1985). But there is also a risk that the contrasting of groups with very different levels of training leads to unwarranted conclusions due to other variables, such as motivation. It should be stressed that all these results concern only measures of variability, not fractal dimension, so they can not guide any predictions for the present experiment. Individual differences must therefore remain an open question.

Second, there is also the possibility of short-term training effects across repeated trials. To both long-term and short-term training applies the question whether estimates of H for the ISIP process are reliable enough to yield them statistically significant. The confidence intervals for independent samples of a pure fGn process decreases of course with N, and remains rather large even for N that can feasibly be produced in sequence by humans. A sufficient number of replications should therefore be made to determine if statistically significant differences can be established among the experimental conditions.

Third, to what extent is fGn a valid model for ISIP variability? Methods for the estimation of H have been evaluated with syntheses of pure fGn (see Caccia et al., 1997), as there exists no prototypic process except the random walk and random uncorrelated noise, both with $H = 0.5$. It is not clear how estimates of H are affected by compound processes, as may be expected in empirical data (see however Cannon et al., 1997 for added white noise). A measure of the fit to the theoretically expected process is therefore necessary to evaluate this question,

and it could also be useful to interpret possible differences in H for different IOIs.

Fourth, having people produce very long sequences, either to satiate data-greedy numerical methods (Gilden et al., 1995) or to decrease confidence intervals, may be problematic. It is possible that fatigue or decreasing motivation inflicts variability of a kind that does not occur for typical sequence lengths of 20–50 intervals. The inhibition theory perspective (Smit & van der Ven, 1995; Spearman, 1927), which has been used to account for spontaneous transforms between ambiguous percepts, might be another explanation of serial dependency relevant for repetitive tasks such as ISMS or ISIP. For example, both verbal transforms of phonemes (Tuller, Ding, & Kelso, 1997) and figural transforms of a Necker cube (Long, Toppino, & Kostenbauder, 1983; cf. Pöppel, 1994) are separated by highly variable intervals in the range from a few seconds to approximately one minute. These intervals are anti-correlated, such that long intervals tend to be followed by short intervals and vice versa. In the event that a similar transform between some hypothetical modes of interval production occurs, it could lead to a fractal dependency, such that, for example, IOIs do on average increase or decrease over the course of one inter transform interval. The frequency of perceptual transforms also changes during the course of an inhibition experiment. It is of course desirable to exclude such extraneous processes, and therefore to minimise the length of the response sequences. Again, a measure of the fit to the theoretically expected process could be helpful to evaluate the possibility that inhibition effects contaminate the data.

Methods

Three women and four men with a wide range of music training participated in five sessions each over the course of 3–5 weeks. The apparatus and procedure were similar to what was employed in Study I, except that the participants hit a drum pad with a drumstick held in the preferred hand. One reason for this is that finger tapping for extended periods of time is uncomfortable and may sometimes cause pain in the fingertip. The other reason is that beating with a drumstick appears to yield smaller dispersion than does finger tapping, according to unpublished data. The noise related to such a peripheral manipulation should not be associated with central processes and thus of little interest for the present concerns.

One session comprised two measurement phases separated by a training phase. The measurement phase consisted of four trials, each with one of the IOIs 500, 800, 1,100, and 1,500 ms in random order. These levels of IOI were chosen so as to separate the breakpoints found close to 1 s and 1.4 s in Study I. Each trial required 25 synchronisation beats and 280 continuation beats.

Results and discussion

Only the production data from the measurement phase ($N \geq 256$) are considered here, not data from the synchronisation or training phases. The first and second points above were addressed by the inclusion of two kinds of repeated measures, namely between-session measurements on different days, and within-session measurements within each session. However, there was no significant main effect of either, so these $2 \times 5 = 10$ levels could be regarded as replications. Although this is a relatively small number of data on which to base a mean value, several differences between participants for given levels of IOI were statistically significant. This holds promise for future research, in which even shorter and less demanding response series might yield useful results. The results are summarised in Figure 8, which plots the estimates of H for all 280 series as a function of response IOI.
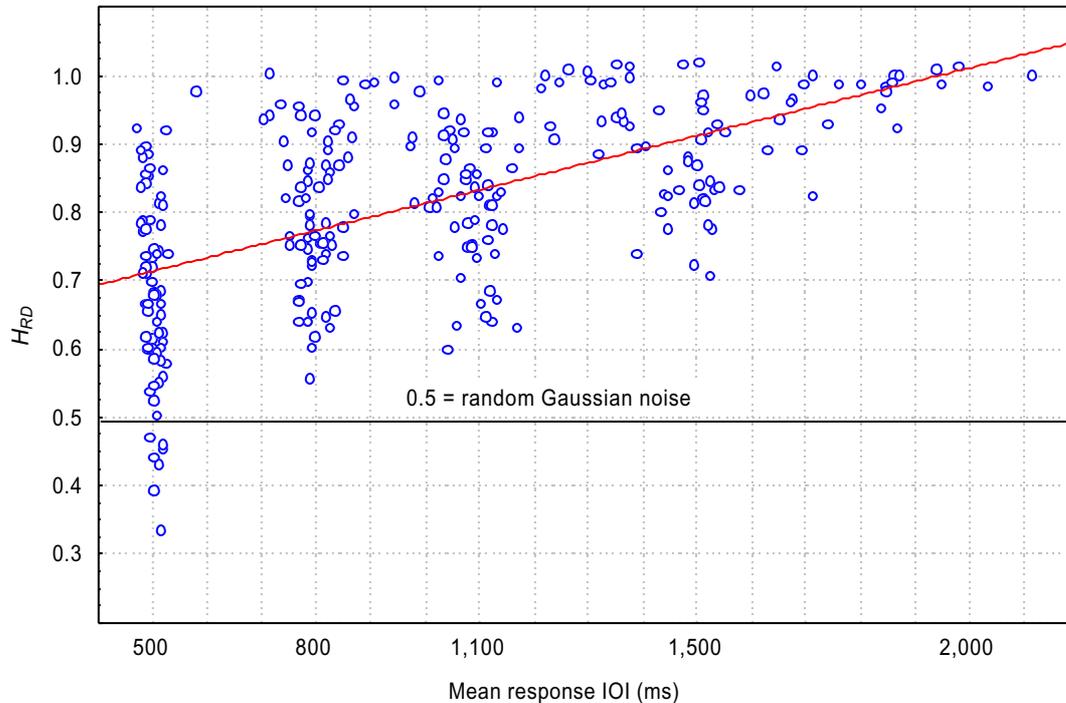
Figure 8. H as a function of the mean IOI for each of the 280 response series, to which a least-squares linear regression line is fitted (reprinted from Study III).

First, H was for most series clearly different from 0.5, with the exception of a few series with 500 ms IOI. According to Table 1, the means for each of the four IOIs across all other variables were more than one .95 confidence interval from 0.5. There were significant effects of participants and IOI, but not of trials and sessions, according to a four-way analysis of variance. The results were therefore broken down in the four levels of IOI for each of the seven participants, which revealed that only in the 500 ms IOI condition for one of the participants was H

not significantly different from 0.5 (0.4980±0.062, $N = 10$, $p = .05$). This participant was male and not musically trained.

Table 1. Mean H and median S_{pe} across trials, sessions, and participants. The rightmost column shows the p-value for the difference in H between that IOI and the next lower level of IOI.

IOI (ms)	H	Md (S_{pe})	Conf. int.	p ($N = 70$)
500	0.6854	0.9702	±0.0331	
800	0.8083	0.9630	±0.0267	< .0001
1,100	0.8460	0.9523	±0.0253	.037
1,500	0.9129	0.9383	±0.0187	< .0001

Note. Confidence intervals are 95%, and p for differences between means is computed with the LSD test ($df = 3, 276$).

Second, the estimate of the fit to the expected variance structure of fGn, S_{pe}, also indicated a good correspondence of ISIP variability to fGn. The values of S_{pe} were centred close to 1.0 across the entire set of 280 series, with 80 percent of the observations being between 0.95 and 1.0 and with a long tail towards lower values. The grand median was 0.969, $Q25$ was 0.934, and $Q75$ was 0.983.

Third, the reliability obtained with only 10 data points suggests that it may be possible to apply local estimates of H to reasonably long ISIP series. This would be a way to assess whether the fractal dimension changes over time, and to explore the time course of such inherent dynamics. It is possible that wavelet transformations will prove suitable for this kind of analysis (Mallat, 1989; Tewfik & Kim, 1992).

Fourth, H increased with IOI as predicted on the basis of Study I. However, this appears not to be a result of a simple one-to-one relation between the drift in Study I and the fractal dimension in Study III. There was no apparent discontinuity within the range 400–850 ms in Study I, whereas the difference in H between 500 and 800 ms IOI was both largest (0.808 - 0.685 = 0.123) and most consistent, in the sense that it was both substantial and in the same direction for all participants. This difference merits further consideration.

It may be that drift and H are entirely uncorrelated, in which case the fractal dimension provides an independent measure of ISIP performance. However, it should be pointed out that drift is correlated with dispersion, and that also H is correlated with dispersion when $H > 0.5$ (Madison, 2000).

Another possibility is that a true change in the operation of the timing mechanism somewhere between 500 and 800 ms IOI leaves too subtle a trace in terms of drift over such short series as in Study I. This is quite conceivable, con-

sidering that there is a substantial amount of temporal noise in the 8–10 Hz range in the motor system (Vallbo & Wessberg, 1993; Wessberg & Vallbo, 1995). Since this noise is most likely constant, or at least independent of parameters with a cognitive interpretation, such as IOI (cf. Wing & Kristofferson, 1973), it may obscure other processes with smaller amplitude.

Given the large individual differences found in Study III, a third possibility is that a number of breakpoints on the individual level between 500 ms and 800 ms smeared each other out in Study I, where the design did not allow individual estimates to be made.

Conclusions

The existence of higher-order dependencies in ISIP appears indisputable in view of the large amount of converging evidence. Also, the reported problems with applying the Wing-Kristofferson model testifies that the assumption of random variability is violated. The question is if and how these dependencies can be characterised. There are as yet very few studies pertaining to this question, and those using spectral analysis (Gilden et al., 1995; Yamada, 1996; Yamada & Tsumura, 1998) have come to different results (cf. Madison, 2000). As mentioned before, methods based on spectral analysis are known to produce spurious results for non-sinusoidal fluctuations, for example due to "side lobe"-effects and quantising noise. It is therefore recommended that peaks at the lowest and highest frequencies in the spectrum be interpreted with great caution, which applies both to Gilden et al.'s and Yamada's conclusions.

As for the relative dispersional method used in Study III, it has been extensively evaluated, but only with synthesised, theoretically correct data (Bassingthwaighte & Raymond, 1995; Caccia et al., 1997; Raymond & Bassingthwaighte, 1999). It has also been used with physiological data, which typically afford much longer data series than those used in Study III, and which are likely to be more long-term consistent than data influenced by cognitive processes. It is therefore not known how estimates of H might be biased by the presence of a trend or step changes, for example. One might intuitively predict that a trend in a limited data series could be taken for the slowest fluctuation in the set, and that it might hence slightly increase H. On the other hand, the portion of the variability pertaining to the trend would probably decrease faster with the bin size m than both $1/m^{0.5}$ and $1/m$, which would give a poor fit according to (9). The effect of adding random noise to a fractal signal is simply a bias towards $H = 0.5$ (Cannon et al., 1997). In conclusion, it seems highly unlikely that the relative dispersion method would spuriously indicate higher-order dependencies or non-randomness.

It must be emphasised that an estimate of fractal dependency does not imply that the observed process is necessarily fractal. Even if S_{pe} indicated a perfect fit

(however unlikely that may be for these relatively short samples), there may nevertheless be minor discontinuities in the dispersion structure that remain obscured due to the low temporal resolution. However, estimates of H sufficiently different from 0.5 do indicate that there is a serial dependency with an approximately corresponding spectrum. Given this, what may the implications be?

First, it may of course have dire consequences for linear methods that assume random variability, and may render conclusions based on such methods invalid. This issue has been discussed in Madison (2000) and will not be pursued here.

Second, estimates of H provide a new source of information regarding motor performance, which according to Study III discriminates among individuals. It might thus be useful as a diagnostic tool even in the absence of a model to explain it.

Third, it might increase our understanding of the basic timing mechanism involved in ISIP, and facilitate its modelling. The most obvious interpretation of serial dependency in the measured process is that each interval is in fact generated on the basis of one or several previous intervals. This idea was discussed by Vroon (1972; 1976) in the context of estimation of time intervals.

A functional model

The reviewed research suggest a number of phenomena that a model of the human timing mechanism should be able to account for, and which have to my knowledge not been considered together. There is a positive, approximately fractal serial dependency in ISIP, except, in some cases, for intervals close to 500 ms. Estimates of this fractal dependency in terms of H increases as a function of IOIs (Study III). There are also discontinuities in timing task performance as a function of interval duration, according to a large body of research. Converging evidence indicates that the temporal resolution decreases stepwise with increasing IOIs, with breakpoints close to 1 s and 1.4 s (e.g. Study I and II). Furthermore, these breakpoints are more strongly related to drift than to negative serial dependency or random variability (Study I). The chapter on duration-specificity did also review a breakpoint close to 1.8 s – possibly extended to 2 s – above which events are no longer perceived as occurring in a sequence.

There is yet another discontinuity in the neighbourhood of 3s, which has only been briefly mentioned in previous chapters, and which might be of relevance for interpreting the pattern of reviewed results. This so-called temporal integration span (TIS), or "presemantic temporal integration" (Pöppel, 1994), will therefore be discussed.

A temporal integration span

As mentioned before, Pöppel (1978; 1988; 1996; 1997) has eloquently argued for the existence of a temporal integration span (TIS) in the neighbourhood of 3 s. This idea goes back to James (the specious present; 1890), Wundt (1911), and the early experiments on grouping or "subjective rhythmization" of metronome sounds (Bolton, 1894; Dietze, 1885; Vierordt, 1868). It is an illusive concept that has been discussed by numerous authors apart from Pöppel, most notably Fraisse (1978; 1982; 1984), Michon (1975; 1978; 1985), and Block (1979; 1990). It is illusive because there are very few empirical data that directly pertain to it, especially in comparison with the large number of treaties on the subject, there exists no clear-cut definition, and it seems impossible to obtain a firm prediction of its duration. However, the main arguments are that the stream of consciousness is segmented in meaningful or at least structurally coherent portions, that the content of these segments is organised in ways that may be suggested by the stimuli, and that both the context and implicit knowledge about the events are incorporated in these processes (Michon, 1978).

One critical point about a TIS is what kind of information it is proposed to integrate. Although the relevant properties from the point of view of the neural system may not be known, it would certainly be possible to distinguish likely

candidates, such as the number of information bits, whether the information is symbolic, semantic, well-known or novel, etc. Without such an organisation of findings from different areas of research, it is not clear how to interpret their apparent similarities. For example, Baddeley (1991; 1992), in his working memory model, proposed a phonological loop of 2 s duration. Since it was derived from, and tested with, semantic material, one can only speculate if it is relevant not only for phonemes but also for other acoustic material. Another example is the eye-hand span in music reading, which contains 5–9 notes that are read ahead of the currently executed music event, and which can be performed even if the music is removed. The eye-hand span varies in leaps related to the position of boundaries in the music (e.g. bar lines) rather than in a continuous flow, and additional structural markers also tend to cause the span to extend exactly to a phrase boundary (Sloboda, 1977; 1984). A similar pattern is also found for typing (Shaffer, 1988).

Thus, both auditory memory, music reading, and typing appears to share a temporal limit which is flexible in response to the properties of the processed information but which is nevertheless typically within the range 2–3 s. These rather vague similarities may of course be superficial, and may be the result of adaptation to similar demands by distinct mechanisms rather than the application of similar mechanisms. Broadly speaking, it seems reasonable that the neural system retains detailed information only so long as it is useful, and then unburdens itself of it to free resources for processing new information. For example, the acoustical signal might have to be represented until phonemes or words have been identified, because the interpretation of a previous sound may depend on the context given by the interpretation of another sound later in a sequence. Likewise, the precise time course of an approaching tennis-ball is required for preparing a stroke on the basis of its predicted time of arrival. After that, a much higher level of abstraction (e.g. "it came from the right and I stroke a backhand") suffices to pursue the game until the next ball is on its way.

The timing patterns in bimanual performance of rhythms may be an example of the TIS. Transitions between regular and irregular deviation patterns among the intervals in a 3:4 polymeter has been found to occur at about 1.9 s pattern duration (which corresponds to 475 and 633 ms IOI for the right and left hand, respectively) (Engbert et al., 1997; Scheffczyk et al., 2000). In the same kind of task, but with highly skilled pianists and different means of analysis, a qualitative shift between integrated and parallel timing was also reported in the range 1–2 s (Krampe et al., 2000).

In conclusion, the converging evidence suggest that it is wiser to expect a TIS than not to expect one, although its properties remain obscure. There are in fact a number of recent studies that report estimates of TIS in terms of the *measured integration interval length* (MIIL), which seems to obtain rather well to serial

timing. Szelag and associates (Szelag, 1997; Szelag et al., 1998; Szelag, von Steinbüchel, Reiser, Gilles de Langen, & Pöppel, 1996; von Steinbüchel, Wittmann, & Szelag, 1999) let people listen to isochronous series of sounds with different IOIs, and indicate how many sound events they could integrate into a unit, either by pressing a button when they experienced the start and end of such a group, or by verbally reporting the number of events. Again, one cannot be certain that this measure taps the same kind of information as is required for comparison of time intervals, because the task did not actually require any precise temporal judgement. For lack of other quantitative data, these results may serve as an approximation and example of the non-linearity typically found, however.

TIS and error correction

The first thing to note about the TIS, according to the description above, is that it should encompass at least two events in order for these to be perceived as a sequence. Thus, the limit of TIS for maximally spaced events should be 3.6–4 s, because the ability to anticipate isochronously spaced events breaks down for IOIs close to 1.8–2 s (Mac Dorman, 1962; Mates et al., 1994; Najenson et al., 1989; Woodrow, 1932). If one instead asks for the perceived grouping into two or more events, a similar limit appears for the duration of the group (Bolton, 1894; Franks & Canic, 1993). Bolton reported an average 1,590 ms for grouping in two intervals, which agrees with Szelag's (1997) non-verbal data seen in Figure 9.

It is reasonable to assume that the perception of sequence is related to the ability to directly compare intervals. If this is the case, then the relation between TIS and IOI determines how many intervals can be compared. The more intervals that fit within the TIS, the higher the order p of error correction (EC) according to $(\text{TIS/IOI}) = p + 1$. At the time of executing an action event, for example, the interval of which this event marks the end must fit into the TIS together with the preceding interval, in order to allow any comparison at all. This corresponds with first-order coupling in time series terminology, and is therefore given the order $p = 1$. Intervals marked by sensory or action events are in a sense discrete: there is little or no information before or after the event. The comparison of intervals requires therefore that at least $p + 1$ intervals fit within the TIS, whereas an additional fraction of an interval makes no difference. The order of EC is hence also discrete, and corresponds with the integer part of $\text{TIS/IOI} - 1$.

Thus, if the TIS were fixed, then the IOIs for each level of p would correspond with the respective integer fraction of TIS. The crosses in Figure 10 depict a hypothetical fixed 2,850 ms integration span, chosen so as to conform with the breakpoints close to 1 s and 1.4 s. However, the results of Szelag and associates indicate that the TIS increases with the IOI, in agreement both with the general

conception of the TIS and the empirical data concerning music reading and typing. The *measured integration interval length* (MIIL), their estimate of the TIS, is plotted in the upper panel of Figure 9, adopted from the studies listed in the legend. Only data pertaining to adults without neural deficits were selected in order to be comparable with the participants used in Studies I–III. MIIL was obtained either by means of verbal (saying a number) and non-verbal responses (pressing a button). Non-verbal responses were only reported in one of these studies (Szelag, 1997), and appears to yield a flatter slope than does verbal responses – in other words a less variable duration. There are obviously substantial differences between the results obtained in the different studies, for which no account is given.

The lower panel of Figure 9 shows the order *p* of the error correction (EC) given by the MIIL estimates. What is interesting is that, although the MIIL functions are quite different across these three studies, the important boundary between *p* = 1 and *p* = 2 is nevertheless equally situated between 500 and 750 ms IOI. Note that the plots for all studies coincide in this region, so that they appear as one line. This means that the kind of EC that can compensate for unintentional errors in the production, such as for example random peripheral delay from the brain to the drumstick's impact on the drumpad, operates for 500 ms IOI but not for 750 ms IOI.
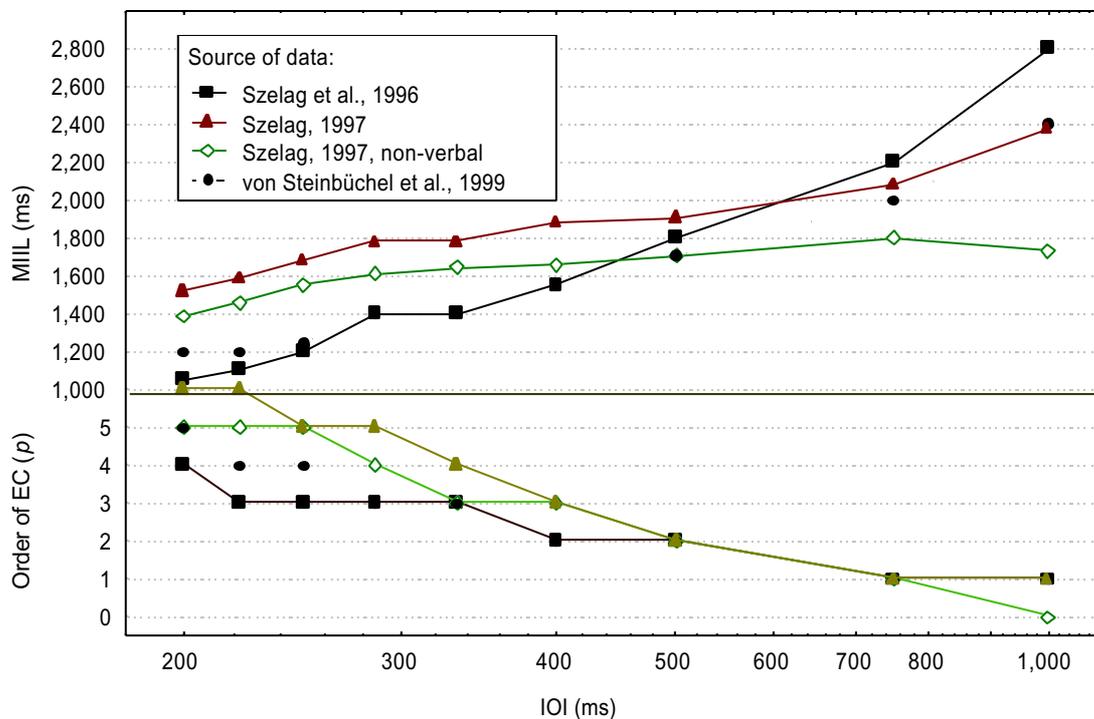
Figure 9. Upper half shows measured integration interval length (MIIL) as a function of IOI, according to each of the three studies in the legend. Lower panel shows the corresponding order $p = \text{MIIL}/\text{IOI} - 1$ of error correction (EC).

Although no IOIs longer than 1 s were used in the studies summarised in Figure 9, one can for the sake of argument extrapolate them to include the critical IOIs close to 1.4 s. It is clear that the data from non-verbal responding will not yield any breakpoint close to 1.4 s, since it does not seem to ever reach $1.4 \times 2 = 2.8$ s. A linear regression was computed for each of the four data sets. Because the slopes of the functions in Figure 9 appear to differ slightly for short and long IOIs, and the extrapolations were only to be applied to longer IOIs, separate regressions were also computed for the 500–1,000 ms portions (except for the non-verbal data, which did not seem to differ much in this respect). If α is the intercept and β is the slope of the regression function, then the order

$$p + 1 = \frac{\alpha + \beta \times \text{IOI}}{\text{IOI}} = \frac{\alpha}{\text{IOI}} + \beta$$

and the critical IOI for a given p can be solved for by

$$\text{IOI}(p) = \frac{\alpha}{p + 1 - \beta},$$

which is plotted in Figure 10. The function based on Szelag et al. (1996) grows faster than twice the IOI, which implies that there is infinite first-order EC. Figure 10 specifies the IOIs for which the important second-order correction engages (~550–770 ms) and suggests that first-order EC engages either close to 900 ms, 1,350 ms, 1,600 ms, or 1,800 ms, depending on which set of results is used.
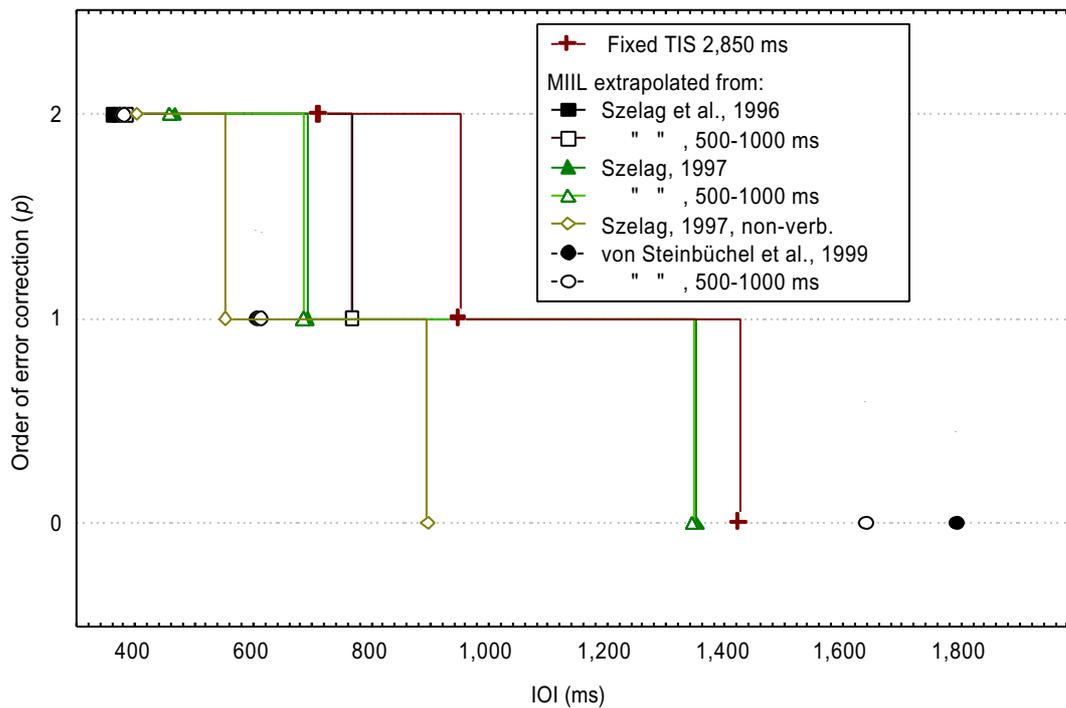
Figure 10. The order *p* of error correction as a function of IOI, according to linear regression functions derived from the data in Figure 9. Crosses depict a hypothetical fixed 2,850 ms integration span, chosen so as to conform with the breakpoints close to 1 s and 1.4 s.

The relatively few and inconsistent data on the TIS means that no firm conclusions can be drawn regarding its relation to EC. It also remains unclear how to interpret the various limits in terms of how many intervals that can actually be compared. The ISMS data suggest that discrete 1.8 s intervals can be anticipated, whereas the rating of sequence data suggest that two intervals must fit within 1.6–2 s. It is possible that the short duration of the events typically used in these studies plays a role in this apparent inconsistency. In order to anticipate, it is only necessary to retain two intervals plus the following event, whereas the perception of sequence may be related to the full cycle or period, that is, including the silent duration of the final interval. In any event, the precise limits need not be known in order to conceive a model which exploits EC.

Time-series modelling

There are several possible ways to describe a model such as the present, for example graphically, mathematically, or as a computer program or flow-chart (e.g. Michon, 1968). A time series framework was chosen, in part because time series modelling is widespread among several disciplines and has a long tradition in timing research. To account for the breakpoints and for the serial dependency, I propose what might be described as a single-interval timer with error correction. To begin with serial dependency, an iterated interval timer may be expected to

produce an uncorrelated random walk. This is simply conceived as an auto-regressive (AR) model in which each interval is equal to its predecessor, plus a white noise process Z with zero mean:

$$X_i = X_{i-1} + Z_i, \quad \mathrm{E}(Z) = 0 \tag{11}$$

This yields Brownian motion (Bm) with the scaling property f^{-2}. Equation 11 is admittedly simplistic with respect to behaviour. For example, duration can not be negative, and intervals between action events are limited by the minimal latency in the neural hardware (~125 ms). However, (11) should be seen as a basic building-block with which to contrast the effects of error-corrective feedback. Note that also the following models have zero expectation to minimise the number of parameters and simplify the notation. Consider the second-order AR model

$$X_i = (1 - \alpha_1)X_{i-1} + \alpha_2 X_{i-2} + Z_i \tag{12}$$

where α are the first- and second-order parameters and Z is a white noise process. It reduces of course to (11) and Bm when $\alpha_1 = \alpha_2 = 0$. However, when $\alpha_1 = -\alpha_2$, this model produces only marginally stable processes. Specifically, Pressing (2000) found that $1/f$ spectra were produced when $\alpha_1 = 1.0$, in other words when there was no first-order coupling at all (since $1 - \alpha_1 = 0$ when $\alpha_1 = 1$), but very strong second-order coupling. This is the result of driving a linear model on the cusp of instability under the influence of random variability, and it is shown as an example that a linear model with error correction can under certain conditions produce the kind of positive serial dependency observed in Study III. That the neural system should ignore first-order EC appears unintuitive, however, which speaks against the plausibility of (12).

Equation 13 might be more intuitively appealing than (12), because weighting the present interval on N and N^2 previous intervals can be interpreted as a retention process. The three terms constitute three different timescales, and this moving average model has been found to produce $1/f$ spectra with α and N in the range 4–6 (Pressing, 2000).

$$X_i = Z_i + \alpha M(Z_i, ..., Z_{i-N}) + \alpha^2 M(Z_i, ..., Z_{i-N^2}) \tag{13}$$

M is the mean, and Z is as usual the white noise process. A simulation with 30 series with each 256 intervals was performed for each combination of α and N in 20 levels. The estimated H according to the relative dispersion method is plotted in Figure 11. Note that the model produces steeper slopes than -1 for α larger than ~6, which saturates the estimation procedure and yields an asymptotic flat region with $H = 1.0$.
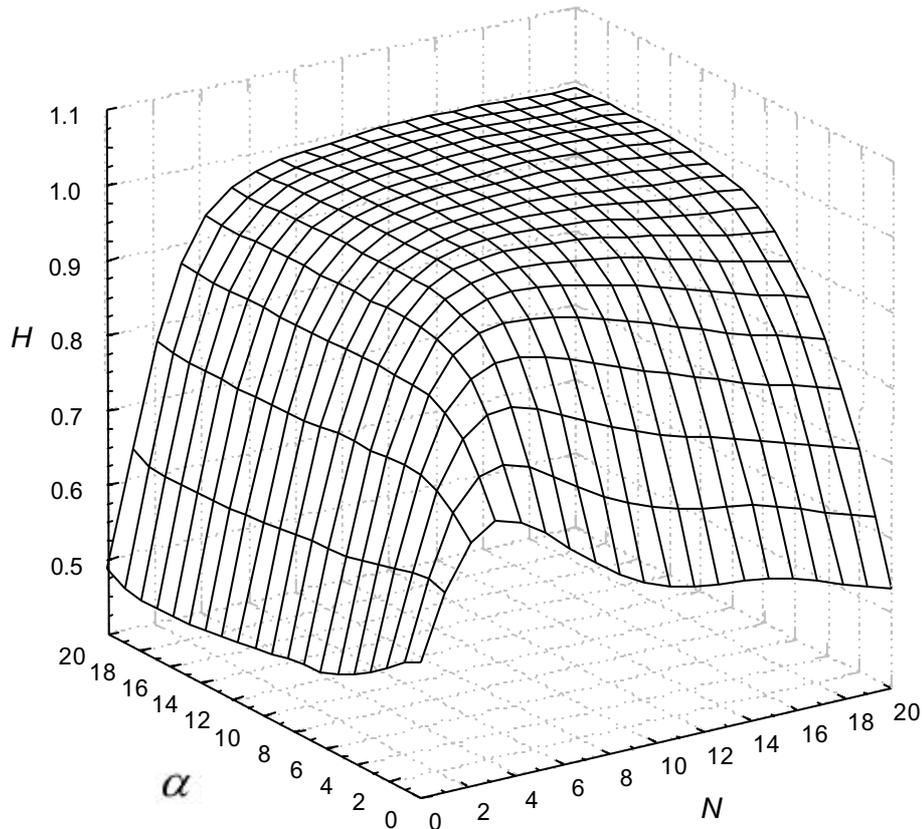
Figure 11. H as a function of α and *N* according to Equation 13, depicted as a distance weighted least-squares fifth order polynomial function, where each point is based on 30 different randomly generated data series. Part of the flat region for α larger than ~6 corresponds with saturation of the relative dispersion procedure.

Equations 10–13 exemplify different ways of obtaining positive serial dependency within a linear time-series framework. There are surely several other ways to do this, some of which might eventually emerge as more consistent with behavioural data. It is possible that an AR model such as (14), with appropriate weights and independent random noise distributions could be fitted to the results of Study III.

$$X_i = (X_{i-1} + Z1_{i-1}) + \alpha_2(X_{i-2} + Z2_{i-2}) + \ldots + \alpha_p(X_{i-p} + Zp_{i-p}) \quad (14)$$

The first-order parameter is given the weight 1.0, in order to produce Bm, but all the higher-order parameters $\alpha_2 - \alpha_p$ are bounded by the interval [–1, 0]. The relative values for $\alpha_2 - \alpha_p$ might change as a function of *p*, although this is not made explicit in (14). Separate white noise processes (Z1, . . , Z*p*) for each order *p* might correspond better with the dynamics of temporal integration than a single noise process (e.g. Haken, 1996; Jirsa, Friedrich, Haken, & Kelso, 1994). How-

ever, such modelling is outside the scope of the present work, whose purpose is simply to demonstrate the suggested effect of error correction.

The drift that occurs in these models should be considered an error by any system with the goal of maintaining constant time intervals. Error correction involves comparing the last few intervals with each other, and applying adjustments in the opposite direction, in other words negative autoregressive parameters. I propose that error correction is applied according to the order of parameters that correspond with the interval duration and the memory of previous intervals, that is, the order $p = \text{TIS/IOI} - 1$. I propose further that the error correction reduces the spectral slope, with breakpoints corresponding with each additional order p.

Without any EC at all ($p = 0$), the current interval can not be directly compared with the previous interval, but it may be based on the less accurate mechanism used for the reproduction of intervals with a few seconds duration (Grondin, 1992; Guay & Salmoni, 1988). With first-order EC, the current interval can be rather precisely timed according to the previous interval, which should on average reduce the amplitude of the long-term drift in relation to the level of short-term random noise. This implies that H is still greater than 0.5, but is now closer to 0.5 than it was without EC. With second-order EC, finally, the last interval can be compared with two previous intervals, which means that compensation for random errors can be made. For example, if the middle interval was made 40 ms shorter than the first, then the last interval can be made 80 ms longer to compensate for that. This way, the process can theoretically become stationary when p ≥ 2, which according to Figure 10 would be predicted for IOI < 600 ms. This was indeed the case for some of the 500 ms series in Study III, whereas the mean H was close to 1.0 for the longest IOIs. Because the ISIP process was characterised as fGn rather than fBm, a H close to 1.0 corresponds with a slope f^{-1} (rather than f^{-3}). Now, as the IOI decreases, and the order of the error correction process hypothetically increases, the mean H was in Study III reduced to 0.685 for 500 ms IOI, which corresponds with an even flatter slope of $f^{-0.37}$. This scheme can be given the general ARMA (autoregressive and moving average) form in (15), combining (13) for generating fractal dependency with AR error correction parameters to reduce it. It may also be realistic to include the independent white noise P to yield a negative first-order process corresponding with the peripheral component in the Wing-Kristofferson model. Consider

$$X_i = Z_i + \alpha M(Z_i, ..., Z_{i-N}) + \alpha^2 M(Z_i, ..., Z_{i-N^2}) - bX_{i-1} - cX_{i-2} + d(P_i - P_{i-1}) \quad (15)$$

where b, c and d are the respective weights. A simulation was performed with α and N both equal to 4, based on the results shown in Figure 11, and b and c in the

interval $[0, 1]$. Z and P were Gaussian white noise processes with $E = 0$ and unit variance:

$$X_i = Z_i + 4M(Z_i, ..., Z_{i-4}) + 16M(Z_i, ..., Z_{i-16}) - bX_{i-1} - cX_{i-2} + (P_i - P_{i-1}) \quad (16)$$

The results showed that higher weights did indeed lead to smaller estimates of H, and that b and c did approximately contribute equally in this respect. Figure 12 therefore plots the mean H across 30 series with 256 points each according to (16) and

$$w = [0.2, 0.25, ..., .95]$$
$$b = \begin{cases} w & \text{if } p \geq 1 \\ 0 & \text{otherwise} \end{cases},$$
$$c = \begin{cases} w & \text{if } p \geq 2 \\ 0 & \text{otherwise} \end{cases}$$

which suggests a good agreement with the results from Study III when $b = c \approx 0.7$.
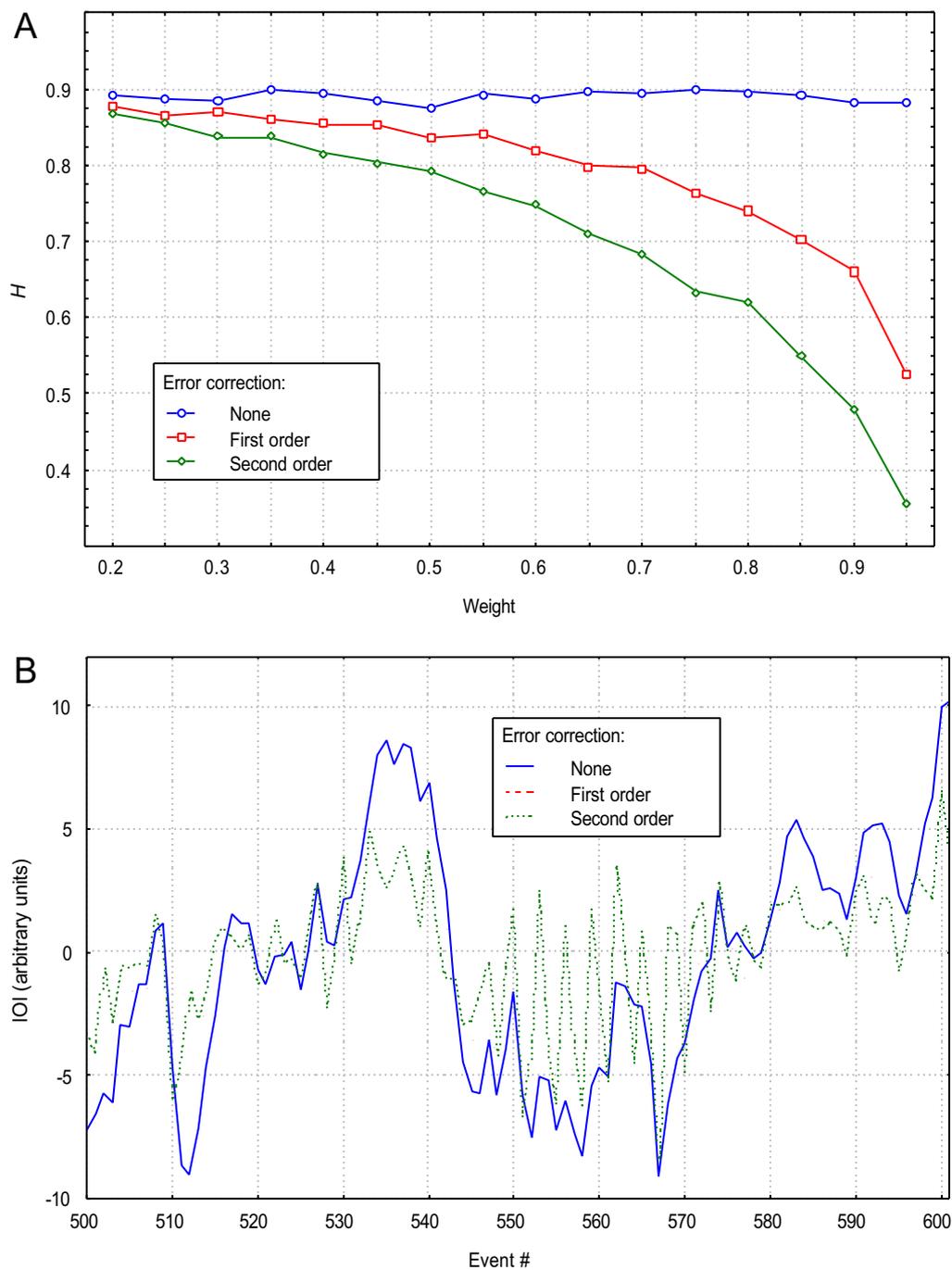
Figure 12. A. *H* as a function of the weight for the AR weights in Equation 16, for zero-, first- and second-order error correction. B. An example of a simulated time series with $b = c \approx 0.7$.

Conclusions

The present chapter represents only one possible interpretation of the data and does furthermore not aspire to provide a full-fledged model. However simplistic, the time series approach has been employed to describe a possible principle underlying the functional dynamics observed in long-term timing behaviour. Indeed, much of the results motivating this principle are novel, and further research to confirm and extend them are necessary. Nevertheless, I feel that they strongly suggest a pattern that might be useful for the generation of hypotheses for future research.

The classical and widespread conception of an "internal clock" as the basis for human timing has repeatedly run into trouble, as discussed in the previous chapters. It may actually be unfair to hold its promoters responsible for these problems, because the concept provides an irresistible image of a balance-wheel, and hands slowly moving in accumulation of its ticks. Maybe has this image not been intended to be taken literally, thus furnishing human timing with features of a mechanical clock: the summation of many small units of time to yield larger units of time, serial independence, and independence of the timed duration across a very wide range. The reported violations of these assumptions highlight the distinction between open-loop (i.e. an oscillator) and closed-loop (i.e. a feedback loop) timing models, by reminding of the fact that an intrinsically closed-loop mechanism can appear to operate in an open-loop fashion if there is error-corrective feedback.

Although I have argued that an interval timer is more neurally plausible and more likely to operate in closed-loop than is a clock-counter, it should be made clear that the two issues are not necessarily connected. There are no damning theoretical arguments against an open-loop interval timer or a closed-loop clock-counter. However, there are results that suggest the existence of the kind of neural structures that may be used for interval timers. Single-cell readings in the ferret auditory cortex reveals a sensitivity for frequencies as low as 1 Hz (which was the lowest f used) (Shamma, Fleshman, Wiser, & Versnel, 1993). Similarly long durations seem also to be neurally implemented in humans, as suggested by responses to rippled noises (Yang, Wang, & Shamma, 1992). In agreement with Todd's (1999; Todd et al., 1999) assertion, then, the apparatus for time need not necessarily require a clock-counter.

A general consequence of a mechanism based on feedback is a strong dependency between action and perception (cf. Ivry & Hazeltine, 1995). If the feedback is mediated by a sensory system reporting the outcomes of actions, such as audition for the stroke of a stick on a drum, or vision for the trajectory of a ball being juggled, then any possible delay can in principle be adjusted for. This flexibility would be sacrificed if the feedback was given on a cortical level

(compensating for random neural delays, cf. Miall, 1996) or a kinaesthetic level (compensating for peripheral neural delay and limb dynamics). There is indeed some evidence that the subjective time for one's own actions has a proprioceptive origin (Jirsa, Radil, & Maras, 1992).

Redundancy is a hallmark of brain functioning, and it is therefore conceivable that each modality acts as a parallel link in the system and produces similar results. The differences between the trading of one modality for another should therefore be related to the temporal resolution of that modality (Kolers & Brewster, 1985) rather than to different mechanisms, as was discussed on page 26.

Although only one model has been considered, a number of questions and suggestions for future work have been raised. First of all, it remains to be seen how well this kind of simple feedback model might be able to account for empirical data, if developed to a sufficient state of sophistication to provide synthesised human-like data. More detailed analyses of ISIP data are required to yield enough information so as to warrant numerical modelling along the proposed lines. For example, how to implement each order of error correction appeared to be rather arbitrary in view of the present knowledge.

An additional concern is the amount of noise in the data, as might be expected from a biological system. Since the mathematical methods for estimating H are developed and mostly tested on synthesised, theoretically correct or generally well-behaved data, it may be desirable to detect and remove outliers in the data on the basis of the fGn model. The fact that an ISIP series is a sample which may contain linear drift also raises the question which effects detrending might have for H and S_{pe} in cases where a true linear trend is removed, compared with cases where the removed trend was in fact part of the fGn process.

Discussion and questions

One challenging aspect of timing research is that time is the primordial variable, which pertains to almost every possible psychological phenomenon. The sheer amount of potentially relevant studies is therefore immense. Well-defined demarcations are very difficult to make, and will probably anyhow be inappropriate with respect to the core of the matter. Although the inclusion of literature citations has been conservative, I argue that the possible scientific value of this work lies primarily with its ascent above the task-specific. In order not to exceed the present scope, I have intentionally left out two relevant issues. The first is dynamical structuring, for example timing effects of temporal or other patterns, such as the structure implied by pitches, harmonies, and durations in music, but also effects of extensive training in terms of musical skill or repeated exposure to a specific piece of music. The second issue is the growing body of brain localisation studies, based on brain lesions, EEG, PET, or fMRI. This may be justified by the fact that the link between brain activation and the behavioural data appears generally weak or inconclusive from the point of view of the present work. The prime variable in these studies is dispersion, or possibly central and peripheral dispersion according to the Wing-Kristofferson model, all of which have little to say about higher-order dependencies. In general, data from brain localisation studies are as yet quite preliminary with respect to timing, and I believe that much more different studies are required for sensible patterns to emerge. It is furthermore absolutely essential for brain imaging studies to be firmly guided by well-defined hypotheses in order to yield useful results, and such hypoteses are largely wanting.

A persistent problem for modelling biological systems in general is the conceptual rift between neural functioning and the modelling language. The latter is more often than not a mathematical one, whose strengths as an analytical tool may provide caveats when the subject matter has a number of different constraints. For example, neural elements have more or less general limits in their temporal and activational dynamics and resolution, which are cumbersome to model, and which may in any case be unknown or incorrectly estimated. More importantly, the aspects of the system which are typically available for investigation are emergent properties of abundant amounts of elements in ensemble. This does not imply that the basic features of the elements can be entirely eliminated by design. Indeed, the temporal limits should play a central role in the study of timing behaviour. For example, an AR process can easily for certain parameter values spin off to infinitely small or large values, whereas such kind of dynamics does not occur in a neural system which is subject to limits and saturation. In other words, it is conceivable that some of the equilibrium or stability

expected in a dynamical or self-organising system may arise from multiple constraints built into the neural hardware.

I confess to not having a remedy for this problem. The challenge is rather to have a variety of different modelling approaches compete on equal terms with their ability to account for the observed phenomena. It is important to sample and model these phenomena across their entire range of operation. Once a tentative model is proposed, it could also be tested for parameter values outside the ecologically relevant range, which may be a strong case for or against its realism.

This being said, it is clear that such extensive data collection is not feasible with typical experimental design. For example, the inclusion of error correction in the model makes it desirable to replicate Study III with a wider range of IOIs. On the one hand, possible higher orders of error correction might be inferred for very short IOIs. On the other hand, it remains to be seen how close to Brownian motion the process might come for very long IOIs when $p = 0$, and it is bounded only by a lower limit of 100–125 ms. Time estimation and reproduction studies indicate that there is some sort of memory operating even when intervals are separated by more than 3 s, and it would be of outstanding theoretical interest to find out what happens with the fractal dimension under these conditions. Now, the first thing to consider is that a datapoint in the experimental design in Study III was derived from at least 256 responses collected over 2.2–7 minutes (500–1,500 ms IOI). The sampling of this sequence of responses may further be contaminated by outliers, which introduces error variance to be challenged by repeated measures, and so forth. In this situation, one can imagine reaching a point at which natural fluctuations within an individual's performance counteracts the expected increase in statistical significance due to larger numbers of samples. As more dynamical behaviours are considered, more thoughtful experimental design is also required, so as to tap the appropriate level of the phenomenon. For temporal tasks which allow real-time interaction, it might be possible to state and evaluate the hypotheses more directly in terms of this interaction. One can consider experiments that allow interaction within the participant (e.g. Fraisse & Voillaume, 1971) or between participants (e.g. Mates, Radil, & Pöppel, 1992) as half-way examples.

It should once again be stressed that dispersion is a blunt measure of performance. Fractal processes appear to be Gaussian if measured with linear methods, and are therefore easily overlooked. Dispersion has nevertheless been the prime measure in clinical diagnosis and modelling of brain lesions (Annoni & Pegna, 1997; Franz et al., 1996; Ivry & Keele, 1989; Leonard, Milner, & Jones, 1988; Shimoyama et al., 1990; von Steinbüchel, Wittmann, & Pöppel, 1996). Some interesting correlations between timing performance and intelligence have also been suggested (e.g. Smith & McPhee, 1987; Stankov & Crawford, 1993; Szelag et al., 1996; Wearden, Wearden, & Rabbitt, 1997), as between timing and

mental disorder (Stein, 1977). I believe that the nature and validity of these possible relations could be better evaluated with more refined measures, including drift or H. The measure of drift developed in Study I should therefore be carefully evaluated on both synthetic and empirical data to assess its ability to tap the (fractal) dependency in serial timing even with short data series.

Acknowledgements

References

Allan, L. G. (1992). The internal clock revisited. In F. Macar, V. Pouthas, & W. J. Friedman (Eds.), *Time, action and cognition* (pp. 191-202). Dordrecht, the Netherlands: Kluwer.

Allan, L. G., & Gibbon, J. (1991). Human bisection at the geometric mean. *Learning and Motivation, 22*, 39-58.

Annoni, J. M., & Pegna, A. J. (1997). Random motor generation in a finger tapping task: Influence of spatial contingency and of cortical and subcortical hemispheric brain lesions. *Journal of Neurology, Neurosurgery and Psychiatry, 63*, 654-659.

Aschersleben, G., & Prinz, W. (1995). Synchronizing actions with events: The role of sensory information. *Perception & Psychophysics, 57*, 305-317.

Baddeley, A. (1991). *Human memory. Theory and practice*. Hove and London: Lawrence Earlbaum Associates.

Baddeley, A. (1992). Working memory. *Science, 255*, 556-559.

Bak, P. (1997). *How nature works*. Oxford: Oxford University Press.

Barnsley, M. F., Devaney, R. L., Mandelbrot, B. B., Peitgen, H.-O., Saupe, D., & Voss, R. F. (1988). *The science of fractal images*. New York: Springer verlag.

Bartlett, N. R., & Bartlett, S. C. (1959). Synchronization of a motor response with an anticipated sensory event. *Psychological Review, 66*, 203-218.

Bassingthwaighte, J. B., & Beyer, R. P. (1991). Fractal correlation in heterogeneous systems. *Physica D (Nonlinear phenomena), 53*, 71-84.

Bassingthwaighte, J. B., & Raymond, G. M. (1995). Evaluation of the dispersional analysis method rescaled for fractal time series. *Annals of Biomedical Engineering, 23*, 491-505.

Beran, J. (1994). *Statistics for long-memory processes*. New York: Chapman & Hall.

Block, R. A. (1979). Time and consciousness. In G. Underwood & R. Stevens (Eds.), *Aspects of consciousness: Vol.1.Psychological issues* (pp. 179-217). London: Academic Press.

Block, R. A. (1990). Models of psychological time. In R. A. Block (Ed.), *Cognitive models of psychological time.* (pp. 1-35). Hillsdale, NJ: Erlbaum.

Bolton, T. L. (1894). Rhythm. *American Journal of Psychology, 6*, 145-238.

Brown, J. W. (1990). Psychology of time awareness. *Brain and Cognition, 14*, 144-164.

Buonomano, D. V., & Merzenich, M. M. (1995). Temporal information transformed into a spatial code by a neural network with realistic properties. *Science, 267*, 1028-1030.

Caccia, D. C., Percival, D., Cannon, M. J., Raymond, G. M., & Bassingthwaighte, J. B. (1997). Analyzing exact time-series: evaluating dispersional analysis and rescaled range methods. *Physica A, 246*, 609-632.

Cannon, M. J., Percival, D., Caccia, D. C., Raymond, G. M., & Bassingthwaighte, J. B. (1997). Evaluating scaled window variance methods for estimating the Hurst coefficient of time series. *Physica A, 241*, 606-626.

Chaffin, D. G., Goldberg, C. C., & Reed, K. L. (1991). The dimension of chaos in fetal heart rate. *American Journal of Obstretics and Gynecology, 165*, 1425-1429.

Chatfield, C. (1980). *The analysis of time series: An introduction.* (2nd ed.). London: Chapman and Hall.

Chen, Y., Ding, M., & Kelso, J. A. S. (1997). Long memory processes (1/f^a type) in human coordination. *Physical Review Letters, 79*, 4501-4504.

Church, R. M. (1984). Properties of the internal clock. *Annals of the New York Academy of Sciences, 423*, 566-582.

Collier, G. L., & Wright, C. E. (1995). Temporal rescaling of simple and complex ratios in rhythmic tapping. *Journal of Experimental Psychology: Human Perception and Performance, 21*, 602-627.

Collyer, C. E., Broadbent, H. A., & Church, R. M. (1992). Categorical time production: Evidence for discrete timing in motor control. *Perception & Psychophysics, 51*, 134-144.

Collyer, C. E., Broadbent, H. A., & Church, R. M. (1994). Preferred rates of repetitive tapping and categorical time production. *Perception & Psychophysics, 55*, 443-453.

Dávila, D. (1995). *Con el Pañuelo en la Nariz (Caracas y la Influenza de 1918).* Caracas: Historiadores SC.

Dewson III, J. H., & Cowey, A. (1969). Discrimination of auditory sequences by monkeys. *Nature, 222*, 696-697.

Dietze, G. (1885). Untersuchungen über den Umfang des Bewusstseins bei regelmässig auf einander folgenden Schalleindrucken. *Phil.stud, 2*, 362-393.

Drake, C., & Botte, M.-C. (1993). Tempo sensitivity in auditory sequences: Evidence for a multiple-look model. *Perception & Psychophysics, 54 (3)*, 277-286.

Dunlap, K. (1910). Reactions to rhythmic stimuli with attempt to synchronize. *Psychological Review, 17*, 399-416.

Einstein, A. (1905). Über die von der molekularkinetischen Theorie der Wärme geforderte Bewegung von in ruhenden Flüssigkeiten suspendierten Teilchen. *Annual Physics, 322*, 549-560.

Eisler, H. (1975). Subjective duration and psychophysics. *Psychological Review, 82*, 429-450.

Eisler, H. (1976). Experiments on subjective duration 1868-1975: a collection of power function exponents. *Psychological Bulletin, 83*, 1154-1171.

Eisler, H. (1981). The parallel-clock model: Replies to critics and criticisms. *Perception & Psychophysics, 29*, 516-520.

Eisler, H., & Eisler, A. D. (1991). A mathematical model for time perception with experimentally obtained subjective time scales for humans and rats. *Chronobiologia, 18*, 79-88.

Eke, A., Herman, P., Bassingthwaighte, J. B., Raymond, G. M., Percival, D., Cannon, M. J., Balla, I., & Ikrenyi, C. (1999). Physiological time series: distinguishing fractal noises from motions. *European Journal of Physiology, in press*

Ekman, G., & Frankenhaeuser, M. (1957). Subjective time scales. *Reports from the Psychological Laboratories, University of Stockholm, 49*

Engbert, R., Scheffczyk, C., Krampe, R. T., Rosenblum, M., Kurths, J., & Kliegl, R. (1997). Tempo-induced transitions in polyrhythmic hand movements. *Physical Review E, 56*, 5823-5833.

Essens, P., & Povel, D. J. (1985). Metrical and nonmetrical representations of temporal patterns. *Perception & Psychophysics, 37*, 1-7.

Fiala, J. C., Grossberg, S., & Bullock, D. (1996). Metabotropic glutamate receptor activation in cerebellar Purkinje cells as substrate for adaptive timing in the classically conditioned eye-blink response. *The Journal of Neuroscience, 16*, 3760-3774.

Fraisse, P. (1967). Le seuil différentiel de durée dans une suite régulière d'intervalles. *Année Psychologique, 67*, 43-49.

Fraisse, P. (1978). Time and rhythm perception. In E. C. Carterette & M. P. Friedman (Eds.), *Handbook of perception (Vol. 8).* (pp. 203-254). New York: Academic press.

Fraisse, P. (1982). Rhythm and tempo. In D. Deutsch (Ed.), *The psychology of music* (pp. 149-180). London: Academic Press.

Fraisse, P. (1984). Perception and estimation of time. *Annual Review of Psychology, 35*, 1-36.

Fraisse, P., Pichot, P., & Clirirouin, G. (1949). Les aptitudes rhythmiques. Etude comparée des oligophrénes des enfants narmaux. *Journal de Psychologie Normale et Pathologique, 42*, 309-330.

Fraisse, P., & Voillaume, C. (1971). Les repéres du sujet dans la synchronisation et dans la pseudo-synchronisation. *Psychologie Francaise, 71*, 359-369.

Franek, M., Mates, J., Radil, T., Beck, K., & Pöppel, E. (1991). Finger tapping in musicians and nonmusicians. *International Journal of Psychophysiology, 11*, 277-279.

Franks, I. M., & Canic, M. J. (1993). A note on the perceptual grouping of rhythmic sequences. *Human Movement Science, 12*, 235-246.

Franz, E. A., Ivry, R. B., & Helmuth, L. L. (1996). Reduced timing variability in patients with unilateral cerebellar lesions during bimanual movements. *Journal of Cognitive Neuroscience, 8*, 107-118.

Freyd, J. J., & Johnson, J. (1987). Probing the time course of representational momentum. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 13*, 259-268.

Friberg, A., & Sundberg, J. (1995). Time discrimination in a monotonic, isochronous sequence. *Journal of the Acoustical Society of America, 98*, 2524-2531.

Frischeisen-Köhler, I. (1933). *Das Persönliche Tempo. Eine erbliologische Untersuchung.* Leipzig: Thieme.

Garner, W. R., & Gottwald, R. L. (1968). The perception and learning of temporal patterns. *Journal of Experimental Psychology, 20*, 97-109.

Geissler, H. G. (1987). The temporal architecture of central information processing: Evidence for a tentative time-quantum model. *Psychological Research, 49*, 99-106.

Gescheider, G. A. (1997). *Psychophysics: The fundamentals.* Hillsdale, NJ, USA: LEA.

Getty, D. J. (1975). Discrimination of short temporal intervals: A comparison of two models. *Perception & Psychophysics, 18*, 1-8.

Getty, D. J. (1976). Counting processes in human timing. *Perception & Psychophysics, 20*, 191-197.

Gibbon, J., & Church, R. M. (1990). Representation of time. *Cognition, 37*, 23-54.

Gibbon, J., Malapani, C., Dale, C. L., & Gallistel, C. (1997). Toward a neurobiology of temporal cognition: advances and challenges. *Current Opinion in Neurobiology, 7*, 170-184.

Gilden, D. L. (1997). Fluctuations in the time required for elementary decisions. *Psychological Science, 8*, 296-301.

Gilden, D. L. (2001). Cognitive emissions of 1/f noise. *Psychological Review, 108*, 33-56.

Gilden, D. L., Thornton, T., & Mallon, M. W. (1995). 1/*f* noise in human cognition. *Science, 267*, 1837-1839.

Glenberg, A. M., Mann, S., Altman, L., Forman, T., & et al. (1989). Modality effects in the coding and reproduction of rhythms. *Memory and Cognition, 17*, 373-383.

Grondin, S. (1992). Production of time intervals from segmented and nonsegmented inputs. *Perception & Psychophysics, 52*, 345-350.

Grondin, S. (1993). Duration discrimination of empty and filled intervals marked by auditory and visual signals. *Perception & Psychophysics, 54*, 383-394.

Grondin, S., Meilleur-Wells, G., & Lachance, R. (1999). When to start counting in a time-intervals discrimination task: A critical point in the timing process of humans. *Journal of Experimental Psychology: Human Perception and Performance, 25*, 993-1004.

Grondin, S., Meilleur-Wells, G., Oullette, C., & Macar, F. (1998). Sensory effects on jugdments of short time-intervals. *Psychological Research, 61*, 261-268.

Grondin, S., & Rousseau, R. (1991). Judging the relative duration of multimodal short empty time intervals. *Perception & Psychophysics, 49*, 245-256.

Guay, M., & Salmoni, A. W. (1988). Effect of interpolated temporal activity on temporal short-term memory. *Perceptual and Motor Skills, 67*, 743-748.

Haken, H. (1983). *Synergetics: An introduction* . (3 ed.). Berlin: Springer.

Haken, H. (1996). Noise in the brain: a physical network model. *Int.J.Neural Syst., 7*, 551-557.

Halpern, A. R., & Darwin, C. L. (1982). Duration discrimination in a series of rhythmic events. *Perception & Psychophysics, 31*, 86-89.

Handel, S., & Lawson, G. R. (1983). The contextual nature of rhythmic interpretation. *Perception & Psychophysics, 34*, 103-120.

Handel, S., & Oshinsky, J. S. (1981). The meter of syncopated auditory polyrhythms. *Perception & Psychophysics, 30*, 1-9.

Harrel, T. W. (1937). Factors influencing preference and memory for auditory rhythm. *Journal of General Psychology, 17*, 63-104.

Harrington, D. L., Haaland, K. Y., & Hermanowitz, N. (1998). Temporal processing in the basal ganglia. *Neuropsychology, 12*, 3-12.

Hary, D., & Moore, G. P. (1985). Temporal tracking and synchronization strategies. *Human Neurobiology, 4*, 73-77.

Hary, D., & Moore, G. P. (1987). Synchronizing human movement with an external clock source. *Biological Cybernetics, 56*, 305-311.

Hastings, H. M., & Sugihara, G. (1993). *Fractals. A user's guide for the natural sciences*. Oxford: Oxford University Press.

Heglund, N. D., Taylor, R. C., & McMahon, T. A. (1974). Scaling stride frequency and gait to animal size: Mice to horses. *Science, 186*, 1112-1113.

Helmuth, L. L., & Ivry, R. B. (1996). When two hands are better than one: Reduced timing variability during bimanual movements. *Journal of Experimental Psychology: Human Perception and Performance, 22*, 278-293.

Hibi, S. (1983). Rhythm perception in repetitive sound sequence. *Acoustical Society of Japan(E), 4 (2)*, 83-95.

Hulstijn, W., Summers, J. J., van Lieshout, P. H., Peters, H. F., & van Lieshout, P. H. (1992). Timing in finger tapping and speech: A comparison between stutterers and fluent speakers. *Human Movement Science, 11*, 113-124.

Hurst, H. E. (1951). Long-term storage capacity of reservoirs. *Transactions of the American society of civil engineers, 116*, 770-880.

Inhoff, A. W., & Rafal, R. D. (1990). Cerebellar structures and the programming of movement sequences. *Behavioural Neurology, 3*, 87-97.

Ivry, R. B. (1996). The representation of temporal information in perception and motor control. *Current Opinion in Neurobiology, 6*, 851-857.

Ivry, R. B., & Hazeltine, R. E. (1995). Perception and production of temporal intervals across a range of duration: Evidence for a common timing mechanism. *Journal of Experimental Psychology: Human Perception and Performance, 21*, 3-18.

Ivry, R. B., & Keele, S. W. (1989). Timing functions of the cerebellum. *Journal of Cognitive Neuroscience, 1*, 136-152.

Ivry, R. B., Keele, S. W., & Diener, H. C. (1988). Dissociation of the lateral and the medial cerebellum in motor action. *Experimental Brain Research, 73*, 167-180.

James, W. (1890). *The principles of psychology (Vol.1)*. New York: Holt.

Jaskowski, P., Jaroszyk, F., & Hojan-Jezierska, D. (1990). Temporal-order judgments and reaction time for stimuli of different modalities. *Psychological Research, 52*, 35-38.

Jasselette, P., Lejeune, H., & Wearden, J. H. (1990). The perching response and the laws of animal timing. *Journal of Experimental Psychology: Animal Behavior Processes, 16*, 150-161.

Jeka, J. J., Oie, K., Schöner, G., Dijkstra, T., & Henson, E. (1998). Position and velocity coupling of postural sway to somatosensory drive. *Journal of Neurophysiology, 79*, 1661-1674.

Jingu, H. (1989). Numerical processing of duration in temporal tracking behavior. *Japanese Psychological Research, 31*, 169-178.

Jirsa, R., Radil, T., & Maras, L. (1992). Perception of timing of movement-onset in a simple reaction time task. *Neuroreport, 3*, 524-526.

Jirsa, V. K., Friedrich, R., Haken, H., & Kelso, J. A. S. (1994). A theoretical model of phase transitions in the human brain. *Biological Cybernetics, 71*, 27-35.

Jones, P. D., & Briffa, K. R. (1992). Global surface air temperature variations during the twentieth century: Part 1, spatial, temporal and seasonal details. *The Holocene, 2*, 165-179.

Kagerer, F., Ilmberger, J., Pöppel, E., Mates, J., & Radil, T. (1990). Auditory motor synchronization: timing in incremental and decremental rhythmic tapping. *Activitas Nervosa Superior, 32*, 145

Kauranen, K., & Vanharanta, H. (1996). Influences of aging, gender, and handedness on motor performance of upper and lower extremities. *Perceptual and Motor Skills, 82*, 515-525.

Keele, S. W., & Hawkins, H. L. (1982). Explorations of individual differences relevant to high level skill. *Journal of Motor Behavior, 14*, 3-23.

Keele, S. W., Pokorny, R. A., Corcos, D. M., & Ivry, R. B. (1985). Do perception and motor production share common timing mechanisms: A correlational analysis. *Acta Psychologica, 60*, 173-191.

Kien, J., & Kemp, A. (1994). Is speech temporally segmented? Comparisons with temporal segmentation in behavior. *Brain and Language, 46*, 662-682.

Killeen, P. R. (1992). Counting the minutes. In F. Macar, V. Pouthas, & W. J. Friedman (Eds.), *Time, action and cognition* (pp. 203-214). Dordrecht, the Netherlands: Kluwer.

Killeen, P. R., & Weiss, N. A. (1987). Optimal timing and the Weber function. *Psychological Review, 94*, 455-468.

Kohno, M. (1992). Two mechanisms of processing sound sequences. In Y. Tohkura & et al. (Eds.), *Speech perception, production and linguistic structure* (pp. 287-293). Tokyo: Ohmsha.

Kohno, M. (1993). Perceptual sense unit and echoic memory. *International Journal of Psycholinguistics, 9*, 13-31.

Kolers, P. A., & Brewster, J. M. (1985). Rhythms and responses. *Journal of Experimental Psychology: Human Perception and Performance, 11*, 150-167.

Krampe, R. T., Kliegl, R., Mayr, U., Engbert, R., & Vorberg, D. (2000). The fast and the slow of skilled bimanual rhythm production: Parallel versus integrated timing. *Journal of Experimental Psychology: Human Perception and Performance, 26*, 206-233.

Kubovy, M., & Howard, F. P. (1976). Persistence of a pitch-segregating echoic memory. *Journal of Experimental Psychology: Human Perception and Performance, 2*, 531-537.

Kumai, M., & Sugai, K. (1997). Relation between synchronized and self-paced response in preschoolers' rhythmic movement. *Perceptual and Motor Skills, 85*, 1327-1337.

Lehtovaara,A., Saarinen,P., & Järvinen,J. *Psychological studies on twins. II. The psychomotor rhythm: environmental versus hereditary determination*. (1966). Report 3. Helsinki, Finland: University of Helsinki.

Leonard, G., Milner, B., & Jones, L. (1988). Performance on unimanual and bimanual tapping tasks by patients with lesions of the frontal or temporal lobe. *Neuropsychologia, 26*, 79-91.

Liberman, A., & Mattingly, I. (1985). The motor theory of speech perception revised. *Cognition, 21*, 1-36.

Long, M., Toppino, T. C., & Kostenbauder, J. F. (1983). As the cube turns: Evidence for two processes in the perception of a dynamic reversible figure. *Perception & Psychophysics, 34*, 29-38.

Mac Dorman, C. F. (1962). Synchronization with auditory models of varying complexity. *Perceptual and Motor Skills, 15*, 595-602.

Madison, G. (2000). On the nature of variability in isochronous serial interval production. In P. Desain & L. Windsor (Eds.), *Rhythm perception and production* (pp. 95-113). Lisse, the Netherlands: Swets and Zeitlinger.

Madison, G. (in press). Variability in isochronous tapping: higher-order dependencies as a function of inter tap interval. *Journal of Experimental Psychology: Human Perception and Performance*.

Madison,G., & Merker,B. (2000). *On the limits of anisynchrony in pulse attribution*. Manuscript submitted for publication

Madsen, C. K., Duke, R. A., & Geringer, J. M. (1986). The effect of speed alterations on tempo note selection. *Journal of Research in Music Education, 34*, 101-110.

Mallat, S. G. (1989). A theory for multiresolution signal decomposition: The wavelet representation. *IEEE Transactions on pattern analysis and machine intelligence, 11*, 674-693.

Mandelbrot, B. B. (1967). How long is the coast of Britain? *Science, 155*, 636

Mandelbrot, B. B. (1983). *The fractal geometry of nature*. (3 ed.). New York: Freeman & Co.

Mandelbrot, B. B., & van Ness, J. W. (1968). Fractional Brownian motions, fractional noises and applications. *SIAM Review, 10* , 422-437.

Mandelbrot, B. B., & Wallis, J. R. (1968). Noah, Joseph and operational hydrology. *Water Resources Research, 4*, 909-918.

Mandelbrot, B. B., & Wallis, J. R. (1969). Some long-run properties of geophysical records. *Water Resources Research, 5*, 321-340.

Mates, J. (1994a). A model of synchronization of motor acts to a stimulus sequence: I. Timing and error corrections. *Biological Cybernetics, 70*, 463-473.

Mates, J. (1994b). A model of synchronization of motor acts to a stimulus sequence: II. Stability analysis, error estimation and simulations. *Biological Cybernetics, 70*, 475-484.

Mates, J., Radil, T., Müller, U., & Pöppel, E. (1994). Temporal integration in sensori-motor synchronization. *Journal of Cognitive Neuroscience, 6*, 332-340.

Mates, J., Radil, T., & Pöppel, E. (1992). Cooperative tapping: Time control under different feedback conditions. *Perception & Psychophysics, 52*, 691-704.

McGill, W. J. (1962). Random fluctuations of response rate. *Psychometrika, 27*, 3-17.

Meshkova, T. A. (1994). On the nature of interindividual differences in personal tempo in 7-8 year old children. *Voprosy Psikhologii, 1994*, 136-141.

Miall, R. C. (1996). Models of neural timing. In M. A. Pastor & J. Arteida (Eds.), *Time, internal clocks and movement* (pp. 69-94). New York: Elsevier Science.

Michon, J. A. (1964). Studies on subjective duration: I. Differential sensitivity in the perception of repeated temporal intervals. *Acta Psychologica, 22*, 441-450.

Michon, J. A. (1966). Tapping regularity as a measure of perceptual motor load. *Ergonomics, 9*, 401-412.

Michon, J. A. (1967a). Magnitude scaling of short durations with closely spaced stimuli. *Psychonomic science, 9*, 359-360.

Michon, J. A. (1967b). *Timing in temporal tracking*. Assen, the Netherlands: Van Gorcum.

Michon, J. A. (1968). A model of some temporal relations in human behavior. *Psychological Research, 31*, 287-298.

Michon, J. A. (1975). Time experience and memory processes. In J. T. Fraser & N. Lawrence (Eds.), *The study of time II* (pp. 302-313). New York: Springer-Verlag.

Michon, J. A. (1977). Holes in the fabric of subjective time: Figure-ground relations in event sequences. *Acta Psychologica, 41*, 191-203.

Michon, J. A. (1978). The making of the present. In J. E. Requin (Ed.), *Attention and performance* (pp. 89-111). Hillsdale, NJ: Lawrence Earlbaum Associates.

Michon, J. A. (1985). The compleat time experiencer. In J. A. Michon (Ed.), *Time, mind, and behavior* (pp. 20-52). Berlin: Springer-Verlag.

Michon, J. A. (2000). Processing of temporal information and the cognitive theory of time experience. In J. T. Fraser, F. C. Haber, & G. H. Müller (Eds.), *The study of time* (pp. 242-258). Heidelberg: Springer.

Michon, J. A., & Van der Valk, N. J. L. (1967). A dynamic model of timing behavior. *Acta Psychologica, 27*, 204-212.

Middleton, F. A., & Strick, P. L. (1994). Anatomical evidence for cerebellar and basal ganglia involvement in higher cognitive function. *Science, 266*, 458-461.

Mishima, J. (1965). *Introduction to the morphology of human behavior. The experimental study of the mental tempo*. Tokyo: Tokyo publishing.

Moore, J. W. (1992). A mechanism for timing conditioned responses. In F. Macar, V. Pouthas, & W. J. Friedman (Eds.), *Time, action and cognition* (pp. 229-238). Dordrecht, the Netherlands: Kluwer.

Najenson, T., Ron, S., & Behroozi, K. (1989). Temporal characteristics of tapping responses in healthy subjects and in patients who sustained cerebrovascular accident. *Brain, Behavior and Evolution, 33*, 175-178.

Nicholson, T. E. (1925). Increase and decline in speed and control of voluntary motor ability. Unpublished PhD thesis, Indiana University, Bloomington;

Niklas, K. J. (1994). *Plant allometry*. Chicago: The University of Chicago Press.

O'Boyle, D. J., Freeman, J. S., & Cody, F. W. (1996). The accuracy and precision of timing of self-paced, repetitive movements in subjects with Parkinson's disease. *Brain, 119*, 51-70.

Ogden, R. T., & Collier, G. L. (1999). On detecting and modeling deterministic drift in long run sequences of tapping data. *Communications in Statistics - Theory and Methods, 28*, 977-987.

Pearson, K. (1902). On the mathematical theory of errors of jufdement, with special reference to the personal equation. *Philosophical Transactions of the Royal Society.Series A, 198*, 235-299.

Peters, M. (1989). The relationship between variability of intertap intervals and interval duration. *Psychological Research, 51*, 38-42.

Post, A. A., Daffertshofer, A., & Beek, P. J. (2000). Principal components in three-ball cascade juggling. *Biological Cybernetics, 82*, 143-152.

Povel, D. J. (1984). A theoretical framework for rhythm perception. *Psychological Research, 45*, 315-337.

Pressing, J. (1999). The referential dynamics of cognition and action. *Psychological Review, 106*, 714-747.

Pressing, J. Sources for 1/f noise effects in human cognition and performance. In Anonymous. *Proceedings of the 4th Conference of the Australasian Cognitive Science Society:*

Pressing, J., & Jolley-Rogers, G. (1997). Spectral properties of human cognition and skill. *Biological Cybernetics, 76*, 339-347.

Pöppel, E. (1978). Time Perception. In R. Held, H. W. Leibowitz, & H.-L. Teuber (Eds.), *Handbook of Sensory Physiology, Vol 8* (pp. 713-729).

Pöppel, E. (1988). *Mindworks: Time and conscious experience*. Boston: Harcourt Brace Jovanovich.

Pöppel, E. (1994). Temporal mechanisms in perception. *International Review of Neurobiology, 37*, 185-202.

Pöppel, E. (1996). Reconstruction of subjective time on the basis of hierarchically organized processing system. In M. A. Pastor & J. Arteida (Eds.), *Time, internal clocks and movement* (pp. 165-185). New York: Elsevier Science.

Pöppel, E. (1997). A hierarcical model of temporal perception. *Trends in Cognitive Sciences, 1*, 56-61.

Rammsayer, T. H., & Lima, S. D. (1991). Duration discrimination of filled and empty auditory intervals: Cognitive and perceptual factors. *Perception & Psychophysics, 50*, 565-574.

Rao, S. M., Harrington, D. L., Haaland, K. Y., Bobholz, J. A., & Cox, R. C. (1997). Distributed neural systems underlying the timing of movements. *The Journal of Neuroscience, 17*, 5528-5535.

Raymond, G. M., & Bassingthwaighte, J. B. (1999). Deriving dispersional and scaled windowed variance analyses using the correlation function of discrete Gaussian noise. *Physica A, 265*, 85-96.

Reitan, R. M., & Wolfson, D. (1993). *The Halstead-Reitan neuropsychological test battery: Theory and clinical interpretation*. (2 ed.). Tucson, AZ: Neuropsychology press.

Schab, F. R., & Crowder, R. G. (1989). Accuracy of temporal coding: Auditory-visual comparisons. *Memory and Cognition, 17*, 384-397.

Scheffczyk, C., Zaikin, A., Rosenblum, M., Engbert, R., Krampe, R. T., & Kurths, J. (2000). Modeling qualitative changes in bimanual movements. *International Journal of Bifurcation and Chaos, 7*, 1441-1450.

Schepers, H. E., van Beek, J. H. G. M., & Bassingthwaighte, J. B. (1992). Four methods to estimate the fractal dimension from self-affine signals. *IEEE Engineering in Medicine and Biology, 11*, 57-71.

Semjen, A., Schulze, H. H., & Vorberg, D. (2000). Timing precision in continuation and synchronization tapping. *Psychological Research, 63*, 137-147.

Sevcik, C. (1998). A procedure to estimate the fractal dimension of waveforms. *Complexity International, 5*

Shaffer, L. H. (1988). Forced revision in fast typing: A note. *Quarterly Journal of Experimental Psychology: Human Experimental Psychology, 40A*, 581-589.

Shamma, S., Fleshman, J., Wiser, P., & Versnel, H. (1993). Response area organization in the ferret primary auditory cortex. *Journal of Neurophysiology, 69*, 367-383.

Shimoyama, I., Ninchoji, T., & Uemura, K. (1990). The finger-tapping test: A quantitative analysis. *Archives of Neurology, 47*, 681-684.

Sloboda, J. (1977). Phrase units as determinants of visual processing in music reading. *British Journal of Psychology, 68*, 117-124.

Sloboda, J. (1984). Experimental studies of musical reading: A review. *Music Perception, 2*, 222-236.

Smit, J. G., & van der Ven, A. H. G. S. (1995). Inhibition in speed and concentration tasts: The Poisson inhibition model. *Journal of Mathematical Psychology, 39*, 265-274.

Smith, G. A., & McPhee, K. (1987). Performance on a coincidence timing task correlates with intelligence. *Intelligence, 11*, 161-167.

Spearman, C. (1927). *The abilities of man*. London: Macmillan.

Stankov, L., & Crawford, J. D. (1993). Ingredients of complexity in fluid intelligence. *Learning and Individual Differences, 5*, 73-111.

Stein, J. (1977). Tempo errors and mania. *American Journal of Psychiatry, 134*, 454-456.

Steinmetz, J. E. (1990). Classical nictitating membrane conditioning in rabbits with varying interstimulus intervals and direct activation of cerebellar mossy fibers as the CS. *Behavioral Brain Research, 38*, 97-108.

Stevens, L. T. (1886). On the time-sense. *Mind, 11*, 393-404.

Stroud, J. M. (1955). The fine structure of psychological time. In H. Quastler (Ed.), *Information theory in Psychology: Problems and methods* (pp. 174-205). Glencoe, Ill.: The Free Press.

Szelag, E. (1997). Temporal integration of the brain as studied with the metronome paradigm. In H. Atmanspacher & E. Ruhnau (Eds.), *Time, temporality, now. Experiencing time and concepts of time in an interdisciplinary perspective* (pp. 121-131). Berlin, Germany: Springer Verlag.

Szelag, E., Kowalska, J., Rymarczyk, K., & Pöppel, E. (1998). Temporal integration in a subjective accentuation task as a function of child develoment. *Neuroscience Letters, 257*, 69-72.

Szelag, E., von Steinbüchel, N., Reiser, M., Gilles de Langen, E., & Pöppel, E. (1996). Temporal constraints in processing of nonverbal rhythmic patterns. *Acta Neurobiologiae Experimentalis, 56*, 215-225.

Tass, P., & Haken, H. (1996). Synchronized oscillations in the visual cortex--a synergetic model. *Biological Cybernetics, 74*, 31-39.

Tewfik, A. H., & Kim, M. (1992). Correlation structure of the discrete wavelet coefficients of fractional Brownian motion. *IEEE Transactions on Information Theory, 38*, 904-909.

Thaut, M. H., Rathbun, J. A., & Miller, R. A. (1997). Music versus metronome timekeeper in a rhythmic motor task. *International Journal of Arts Medicine, 5*, 4-12.

Thompson, R. K. R. (1976). Performance of the bottlenose dolphin (Tursiops truncatus) in delayed auditory sequences and delayed auditory successive discriminations. PhD thesis, University of Hawaii;

Todd, N. P. M. (1996). An auditory cortical theory of primitive auditory grouping. *Network: Computation in neural systems, 7*, 349-356.

Todd, N. P. M. (1999). Motion in Music: A neurobiological perspective. *Music Perception, 17*, 115-126.

Todd,N.P.M., & Cousins,R. (1999). Is beat induction mediated by an internal representation of the body? Evidence for a sensory-motor theory of rhythm perception. *No Journal Found,*

Todd, N. P. M., Lee, C. S., & O'Boyle, D. J. (1999). A sensory-motor theory of rhythm, time perception and beat induction. *Journal of New Music Research, 28*, 5-29.

Treisman, M. (1963). Temporal discrimination and the indifference interval: Implications for a model of the "internal clock.". *Psychological Monographs, 77*

Treisman, M., & Brogan, D. (1992). Time perception and the internal clock: Effects of visual flicker on the temporal oscillator. *European Journal of Cognitive Psychology, 4*, 41-70.

Triplett, D. (1931). The relation between physical pattern and the reproduction of short temporal intervals: A study in the perception of filled and unfilled time. *Psychological Monographs, 41*, 201-265.

Truman, G., & Hammond, G. R. (1990). Temporal regularity of tapping by the left and right hands in timed and untimed finger tapping. *Journal of Motor Behavior, 22*, 521-535.

Tuller, B., Ding, M., & Kelso, J. A. S. (1997). Fractal timing of verbal transforms. *Perception, 26*, 913-928.

Vallbo, Å. B., & Wessberg, J. (1993). Organization of motor output in slow finger movements in man. *Journal of Physiology, 469*, 673-691.

Vierordt, K. (1868). *Der Zeitsinn nach Versuchen [Research on the time sense]*. Tübingen: Laupp.

Voillaume, C. (1971). Modéles pour l'étude de la régulation de mouvements cadencés. *Année Psychologique, 71*, 347-358.

Vollrath, M., Kazenwadel, J., & Krüger, H.-P. (1992). A universal constant in temporal segmentation of human speech. *Naturwissenshaften, 79*, 479-490.

von Baer, K. E. (1864). Welche Auffassung der lebendigen Natur ist die richtige? Und wie ist diese Auffassung auf die Entomologie auzuwenden? In H. Schmitzdorff

(Ed.), *Reden gehalten in wiss. Versammlungen und kleine Aufsätze vermischten Inhalts* (pp. 237-284). S:t Petersburg: Verlag der kaiserl. Hofbuchhandlung.

von Steinbüchel, N., Wittmann, M., & Pöppel, E. (1996). Timing in perceptual and motor tasks after disturbances of the brain. In M. A. Pastor & J. Arteida (Eds.), *Time, internal clocks and movement* (pp. 281-304). New York: Elsevier Science.

von Steinbüchel, N., Wittmann, M., & Szelag, E. (1999). Temporal constraints of perceiving, generating, and integrating information: Clinical indications. *Restorative Neurology and Neuroscience, 14*, 167-182.

Vorberg, D., & Hambuch, R. (1978). On the temporal control of rhythmic performance. In J. E. Requin (Ed.), *Attention and performance VII* (pp. 535-555). Hillsdale, NJ: Erlbaum.

Vorberg, D., & Hambuch, R. (1984). Timing of two-handed rhythmic performance. *Annals of the New York Academy of Sciences, 423*, 390-406.

Vorberg, D., & Wing, A. M. (1996). Modeling variability and dependence in timing. In H. Heuer & S. W. Keele (Eds.), *Handbook of perception and action. Vol. 3. Motor skills* (pp. 181-262). London: Academic Press.

Vos, P. G., & Ellerman, H. H. (1989). Precision and accuracy in the reproduction of simple tone sequences. *Journal of Experimental Psychology: Human Perception and Performance, 15*, 179-187.

Vos, P. G., van Assen, M., & Franek, M. (1997). Perceived tempo change is dependent on base tempo and direction of change: Evidence for a generalized version of Schulze's (1978) internal beat model. *Psychological Research, 59*, 240-247.

Vroon, P. A. (1972). Some psychophysical and cognitive aspects of the time sense. Rijkuniversiteit te Utrecht;

Vroon, P. A. (1976). Sequential estimation of time. *Acta Psychologica, 40*, 475-487.

Wallin, J. E. W. (1911). Experimental studies of rhythm and time. I. *Psychological Review, 18*, 100-131.

Warren, R. M. (1993). Perception of acoustic sequences: global integration versus temporal resolution. In S. McAdams & E. Bigand (Eds.), *Thinking in sound. The cognitive psychology of human audition* (pp. 37-68). Oxford, UK: Clarendon Press.

Warren, R. M., Bashford Jr, J. A., & Gardner, D. A. (1990). Tweaking the lexicon: organization of vowel sequences into words. *Perception & Psychophysics, 47*, 423-432.

Warren, R. M., Gardner, D. A., Brubaker, B. S., & Bashford Jr, J. A. (1991). Melodic and nonmelodic sequences of tones: effects of duration on perception. *Music Perception, 8*, 277-290.

Wearden, J. H. (1991). Do humans possess an internal clock with scalar timing properties? *Learning and Motivation, 22*, 59-83.

Wearden, J. H. (1999). "Beyond the fields we know...": Exploring and developing scalar timing theory. *Behavioural Processes, 45*, 3-21.

Wearden, J. H., Edwards, H., Fakhri, M., & Percival, A. (1998). Why "sounds are judged longer than lights": Application of a model of the internal clock in humans. *Quarterly Journal of Experimental Psychology: Comparative and Physiological Psychology, 51B*, 97-120.

Wearden, J. H., & McShane, B. (1988). Interval production as an analogue of the peak procedure: Evidence for similarity of human and animal timing processes. *Quarterly Journal of Experimental Psychology: Comparative and Physiological Psychology, 40*, 363-375.

Wearden, J. H., Wearden, A. J., & Rabbitt, P.-M. A. (1997). Age and IQ effects on stimulus and response timing. *Journal of Experimental Psychology: Human Perception and Performance, 23*, 962-979.

Weigend, A. S., & Gershenfeld, N. A. (1994). *Time series prediction: Forecasting the future and understanding the past*. Reading, Massachusetts: Addison-Wesley.

Wessberg, J., & Vallbo, Å.B. *Evidence that pulsatile motor output in slow finger movements in man is produced by central mechanisms.* (un pub)

Williams, H. G., Woollacott, M. H., & Ivry, R. B. (1992). Timing and motor control in clumsy children. *Journal of Motor Behavior, 24*, 165-172.

Wing, A. M. (1977a). Effects of type of movement on the temporal precision of response sequences. *British Journal of Mathematical and Statistical Psychology, 30*, 60-72.

Wing, A. M. (1977b). Perturbations of auditory feedback delay and the timing of movement. *Journal of Experimental Psychology: Human Perception and Performance, 3*, 175-186.

Wing, A. M., Keele, S. W., & Margolin, D. I. (1984). Motor disorder and the timing of repetitive movements. *Annals of the New York Academy of Sciences, 423*, 183-192.

Wing, A. M., & Kristofferson, A. (1973). Response delays and the timing of discrete motor responses. *Perception & Psychophysics, 14*, 5-12.

Woodrow, H. (1932). The effects of rate of sequence upon the accuracy of synchronization. *Journal of Experimental Psychology, 15*, 357-379.

Woodrow, H. (1934). The temporal indifference interval determined by the method of mean error. *Journal of Experimental Psychology, 17*, 167-188.

Wundt, W. (1911). *Grundzüge der Physiologischen Psychologie, 3*. (6 ed.). Leipzig: Wilhelm Engelmann.

Yamada, M. (1996). Temporal control mechanism in equaled interval tapping. *Applied Human Science, 15*, 105-110.

Yamada, M., & Tsumura, T. (1998). Do piano lessons improve basic temporal controllability of maintaining a uniform tempo? *Journal of the Acoustical Society of Japan (E), 19*, 121-131.

Yang, X., Wang, K., & Shamma, S. (1992). Auditory representations of acoustic signals. *IEEE Transactions on Information Theory, 38*, 824-839.