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The influence of motor system degradation on the control of handwriting movements: A dynamical systems analysis

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Abstract

The complex dynamics of the human hand/arm system need to be precisely controlled to produce fine movements such as those found in handwriting. This study employs dynamical systems analysis techniques to further understand how this system is controlled when it is functioning well and when it is compromised through motor function degradation (e.g. from tremor). Seven people with and 16 people without multiple sclerosis (MS) participated in this study. Tremor was assessed using spirography with participants being separated into "tremor" (6 people with and 1 person without MS; 2 male, 5 female; age range 40–68) and control (1 person with and 15 people without MS; 5 male, 11 female, age range 18–59) groups. Participants wrote the pseudo-word "lanordam" six times on a digitizer, in a quiet as well as a noisy, mildly stressful environment. Velocity profiles of the pen tip for the best four trials were concatenated and analyzed to determine their dimensionality (a measure of the number of control variables) and Lyapunov exponents (a measure of predictability). Results indicate that the velocity profiles for people with tremor were lower dimensional and had less predictable dynamics than for controls, with no effect of sound condition. Interpreted in the context of related research, it was speculated that the lower dimensionality reflected the loss of control of variables related to the minimization of movement variability, resulting in less predictable movements.

PsycINFO classification: 2330
Keywords: Handwriting; Tremor; Dynamical systems analysis; Dimensionality; Fine motor control

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1. Introduction

The human arm is comprised of several joints that need to be precisely coordinated in order to produce smooth, accurate movements. When one limb segment moves, it creates nonlinear interactive torques within the other limb segments. These movement induced interactions need to be accounted for when performing tasks that appear to be simple, such as reaching for a cup of coffee, as well as more complex tasks such as handwriting (Dounskaia, Van Gemmert, & Stelmach, 2000; Hollerbach & Flash, 1982). Healthy people can control the biomechanics of the limb to produce relatively accurate movements, whereas performance deteriorates when people suffer from tremor or diseases such as multiple sclerosis (MS) or Parkinson's disease. An important question in the field of motor control is how the biomechanical system is controlled to achieve the movement goal in healthy systems, and what characterizes loss of control when people suffer motor system degradation. The present experiment utilizes dynamical analysis techniques in order to provide a novel insight into this question. The results are discussed with regards to past findings using more traditional techniques.

1.1. Movement accuracy and motor function degradation

In order to understand motor function degradation, it is important to be cognizant of the features of healthy motor control. Handwriting, for example, is a multi-joint task that requires fine motor control in order to translate an abstract motor memory into a series of muscular and limb movements with the ultimate goal of producing an endpoint trajectory that results in a relatively invariant and recognizable pattern. Past research has identified velocity as an important variable that can be informative about how the CNS organizes and generates structured movements (Longstaff & Heath, 1997; Mottet & Bootsma, 1999). In addition, the analysis of velocity data is preferred over position data in handwriting studies due to the dependence of position data on the exact pattern drawn. In a study of handwriting performance, Longstaff and Heath (1997) found that higher levels of proficiency (e.g. in terms of legibility) were associated with lower levels of inter-trial temporal variability (evaluated using coherency analysis, a measure of the temporal similarity of two time series). This indicates that when performing a rhythmic movement such as handwriting, spatial variability in a stable physical environment is partly due to variability in movement dynamics, with spatial accuracy depending on a minimization of unwanted dynamic noise.

Longstaff and Heath (2000) extended this research by investigating the ability of people with motor function degradation (as evidenced by the presence of tremor) to consistently produce handwriting movements both under normal conditions and under conditions of mild stress. As predicted, people with tremor exhibited greater inter-trial temporal variability of velocity and pressure profiles in all conditions. When writing in mildly stressful conditions (elicited by the presence of a loud, annoying sound) the people with tremor maintained or decreased their coherency while the control group increased their coherency. These changes in performance were associated with appropriate and adaptive changes in pen pressure for the controls, but inappropriate and detrimental changes for the people with tremor. In the low stress condition, the level of pressure was similar for both groups. However, in the mild stress condition people without tremor increased pen pressure, while the people with tremor tended to decrease their pen pressure. The results were interpreted as evidence that people with motor function degradation are less skilled at modulating parameters (such as muscle stiffness and pen pressure) that could adaptively reduce variability in mildly stressful situations.

1.2. Dynamical systems analysis of graphic skills

The behavior of a dynamical system such as limb movements during handwriting can be characterized by the patterns produced by key system variables as they change over time. When there is a discernable pattern, the system is said to evolve around an attractor. Contemporary research in the field of psychology has applied dynamical systems analysis to a variety of paradigms, such as the study of the space–time information processing capability of the cognitive system (Heath, 2000). For example, examination of response time data suggests that the cognitive system may at times contain nonlinear dynamics (Kelly, Heathcote, Heath, & Longstaff, 2001). Heath, Kelly, and Longstaff (2000) argue that modern nonlinear dynamical analysis techniques allow researchers to determine the information complexity of temporal data using physiological and psychological measurements. In studies of psychomotor skills, these features can compliment traditional analysis techniques such as analysis of the mean and variance of movement speed and provide unique insights into how movements are controlled in healthy systems as well as control problems associated with motor function degradation. This is illustrated in a review article by Newell and Vaillancourt (2001) which discusses the utility of a particular dynamical analysis tool (dimensional analysis) in the study of motor learning.

In an experimental situation, the nature of the system (i.e. its attractor) can be reconstructed from a time series of observations (Packard, Crutchfield, Farmer, & Shaw, 1980; Ruelle, 1981; Takens, 1981). A topological equivalent to the state vector $X(t)$ of the system is generated by taking the observable $x(t)$ as the first coordinate, $x(t+\tau)$ as the second and $x(t+(n-1)\tau)$ as the last. τ is known as the delay parameter and n is termed the embedding dimension. The delay is often chosen using known properties of the system and the embedding lag chosen so that each successive point is independent from previous points, for example by making sure they are decorrelated (Takens, 1981; Tsonis, 1992). Once the dynamical system has been reconstructed, its properties can be evaluated by examining features of the attractor. These can include its dimensionality and its Lyapunov spectra. This reconstruction is the necessary first step in the calculation of these indices, which are then used as quantitative measures of the behavior of the system.

The dimension of a time series is a measure of the minimum number of active variables needed to describe how the system evolves locally around its attractor. It can be thought of as a measure of the number of active degrees of freedom and is a guide to the number of variables that are contributing to the observed behavior of the system. Dimensionality analysis can be applied to both linear and nonlinear systems. In the present study the dimensional estimate used is the correlation dimension (see Appendix A). In terms of motor control research, active degrees of freedom are distinct from biomechanical degrees of freedom. Biomechanical degrees of freedom are fixed by the nature of the limb system in a task specific context. However, active degrees of freedom are those variables that are related to the control of the system as its behavior evolves over time.

As noted by Newell and Vaillancourt (2001), several researchers have applied dimensionality analysis to a motor control context (Ganz, Ehrenstein, & Cavonius, 1996; Newell, Gao, & Sprague, 1995; Newell, van Emmerik, Lee, & Sprague, 1993). These include simple rhythmic finger movements (Kay, 1988; Kay, Saltzman, & Kelso, 1991) and the manipulation of pendula under various conditions (Amazeen, 2002; Goodman, Riley, Mitra, & Turvey, 2000; Mitra, Amazeen, & Turvey, 1998; Mitra, Riley, & Turvey, 1997). These studies demonstrate that the dimension of the system under study can change (e.g. during the learning of a skill), and can vary depending on task constraints. Of more direct relevance is a study by Dooijes and Struzik (1994) which applied dimensional analysis to the graphic skill of handwriting. The dimensionality of handwriting (calculated both in its static and dynamic forms) was found to be low and fractional.

While these studies demonstrate that dimensional analysis can be informative, there is some debate about the ability to establish precise dimensional estimates (Albano, Mees, de Guzman, & Rapp, 1987; Rapp, 1994). As an alternative to interpreting the raw values however, it has been argued that dimensional estimates can legitimately be used as a measure of relative dimensionality (Newell & Vaillancourt, 2001; Rapp, 1993). As such, when analyzing these types of dynamical systems, changes in dimensionality or differences between groups and conditions may be more meaningful than the raw values themselves.

A further aspect of a dynamical system that can be studied is the spectrum of Lyapunov exponents (see for example Heath, 2000; Tsonis, 1992; Wolf, Swift, Swinney, & Vastano, 1985). A Lyapunov exponent is a measure of the speed at which initially similar values of a time series diverge over time (i.e. their trajectories diverge). There is a Lyapunov exponent for each dimension of the process, which together constitute the Lyapunov spectrum for the dynamical system. The Lyapunov exponent is related to the unpredictability of the system. A stable system does not have any positive Lyapunov exponents, while a chaotic system has at least one positive Lyapunov exponent. The sum of all Lyapunov exponents of a chaotic system is negative, consistent with the idea that the chaotic attractor is globally stable. The larger the magnitude of the most positive Lyapunov exponent, the more unpredictable the system.

As an extension of research utilizing lower order statistics (e.g. means and standard deviations) and linear time series analysis techniques (Longstaff & Heath, 1997, 2000), Longstaff and Heath (1999) performed nonlinear dynamical analysis on the velocity profiles of pseudo-words written by healthy young adults. They found that handwriting velocity profiles were generated by low dimensional (between 2.5 and 4) systems with a positive maximum Lyapunov exponent and a negative sum of exponents (max = 0.106–0.145, sum = −0.621 to −1.557, expressed in log base-e units). All these results were different to those found when examining several surrogate time series (Theiler, Eubank, Longtin, Galdrikian, & Farmer, 1992) indicating that these results were not merely due to the system being a simple limit cycle with superimposed stochastic physiological noise (consistent with the findings of Mitra et al., 1997, for example). Although the motor output undoubtedly does contain at least some noise (for example resulting from residual motor-unit firing impact through motor unit twitches) in addition to these low dimensional nonlinear dynamics. This finding was robust, with similar results being calculated for all participants, for both horizontal and vertical velocity time series, for single trials and time series created by the concatenation of several trials, using several different data analysis techniques as well as various delay parameters.

It was argued that the velocity profiles of this complex rhythmic skill display nonlinear dynamics and that the characteristics of these dynamics are informative about the cognitive parameters required to produce these movements. When performing motor skills there are several parameters that can be controlled. These can include the speed and size of the movements, the level of force used to perform the movement and limb stiffness. When performing a movement across a surface the influence of friction can also be altered by modulating the pressure we apply to the surface with the limb or tool (e.g. Wann & Nimmo-Smith, 1991). Limb stiffness has been found to be one parameter that can be used to reduce unwanted variability due to physiological noise (van Galen & Schomaker, 1992; van Gemmert & van Galen, 1997). Some or all of these parameters are controlled by healthy motor systems when performing actions in order to maintain accuracy. We argue that degraded motor systems have a reduced ability to control these parameters.

A reduction in control of the motor system is consistent with evidence from studies using dimensional analysis. It has been demonstrated in a number of areas that dimensionality often reduces in the presence of disease (Newell & Vaillancourt, 2001). These include tremor in Parkinson's disease (Vaillancourt & Newell, 2000), epileptic EEG fluctuations (Babloyantz & Destexhe, 1986; Lehnertz & Elger, 1998), as well as in heart rate and blood pressure regulation (Kaplan et al., 1991; Skinner, Carpeggiani, Landisman, & Fulton, 1991). Newell and Vaillancourt (2001) write that these findings imply that a loss of complexity "is reflective of poorer performance and/or less effective (adaptive) system control. The experimental studies, therefore, provide evidence for the idea that reduced dimensionality is an undesirable feature of system change" (p. 707).

The present study elaborates the argument that people suffering from motor function degradation have diminished control over parameters that healthy people can effectively modulate to minimize unwanted movement variability (Longstaff & Heath, 2000). We propose that this reduction in control will be reflected in a psychomotor system that is lower dimensional and less predictable. In terms of the variables analyzed, two specific hypotheses can be stated. If the motor system of people with tremor is indeed more variable than for people without tremor, it would be expected that motor movements would be less predictable than those for healthy people. This reduction in predictability is directly linked to the increase in dynamical variability found in a sample from this population by Longstaff and Heath. Since the largest Lyapunov exponent is a measure of the predictability of a nonlinear system, it is hypothesized that the magnitude of the largest Lyapunov exponent will be greater for people with tremor than for people without tremor. If people with tremor are less able to modulate the control mechanisms that healthy people use to filter out unwanted variability, their handwriting movements are likely to be generated by a lower dimensional process than for controls. It is therefore hypothesized that the dimensionality of the tangential velocity profiles of handwriting movements will be smaller for people with tremor than for controls.

An additional aim of this study is to learn more about the nature and source of the nonlinear dynamics identified in previous studies. If such dynamics represent some stable property of the task related psychomotor/biomechanical system, such as a general ability to accurately control the handwriting movement, then it would be expected that there would be no change in the correlation dimension and Lyapunov exponents when writing under mildly stressful conditions. If however, the dynamics represent a system property that alters due to an increase in neuromotor noise, such as changes in muscle tone or speed of writing, the correlation dimension and Lyapunov exponents should also change. The direction of this change will depend on which system property is altered.

The nonlinear dynamical analysis of handwriting movements by Longstaff and Heath (1999) indicated that each individual had a stable characteristic pattern, representing motor memory for movement control. It is not unreasonable to suggest that such a memory can be represented by dynamics. It is therefore hypothesized that there will be no changes in either the largest Lyapunov exponent or the correlation dimension when writing in a mildly stressful environment. Finally, it is hypothesized that the correlation dimension would be low, the maximum Lyapunov exponent would be positive, and the sum of exponents would be negative. This would provide further evidence for the proposal that handwriting movement dynamics are produced by nonlinear oscillators, rather than limit cycle oscillators with superimposed noise.

2. Method

2.1. Subjects

Seven people with MS and 17 people without MS volunteered to participate in this study, however data from one healthy participant was not used as their writing was considered to be closer to printing than cursive writing. The participants with MS were recruited from the local MS community through contact with the Hunter Council for People with MS. People with MS were recruited as they commonly display symptoms such as tremor (Alusi, Glickman, Aziz, & Bain, 1999; Alusi, Worthington, Glickman, & Bain, 2001; Sandyk & Dann, 1994) that can lead to disturbances in graphic skills such as handwriting and drawing, allowing these tasks to be successfully used as assessment tools (Alusi, Worthington, Glickman, Findley,

& Bain, 2000; Longstaff et al., 2003; Manikel & Girouard, 2000; Persaud, 2002). Motor function was assessed by spirography (Bain & Findley, 1993), a clinical tool for evaluating the degree of tremor severity. Spirography essentially involves comparing spirals drawn by subjects against a standard set of spirals for features that are characteristic of different levels of tremor. Participants were rated as either displaying no tremor (rating 0–1) or some degree of tremor (rating 2–10). As expected, not all MS subjects displayed tremor and not all of the older subjects were tremor free (tremor is not always observed in patients with MS and can occur in otherwise healthy older adults e.g. Louis, Wendt, & Ford, 2000).

Six people with MS and one without MS were rated as displaying some degree of tremor (2 Male, 5 Female, age range 40–68; mean age = 53; mean tremor rating = 3.3, SE = 0.4). The person without MS whose spiral displayed tremor was 63 years old and had noted on a demographic questionnaire that she suffered from tremor. Sixteen people without MS and one with MS were rated as not displaying tremor (5 Male, 12 Female; age range 18–59, mean age = 30; mean tremor rating = 0.8, SE = 0.1). The person with MS whose spiral did not display tremor was 44 years old and had noted on a demographic questionnaire that she did not suffer from tremor. Therefore there were two groups of participants, seven people with tremor and sixteen people without tremor. A t-test determined that the people in the tremor group were rated as displaying significantly more tremor than the people in the nontremor group $t(6) = 5.83$, $p < 0.01$. Since there is a difference in mean age between the groups, linear regression analysis was used to determine if there were significant relationships between the age of the participants and the dependent variables. When there was a significant relationship, age was used as a covariate in the following analysis. This experiment was carried out according to the ethical guidelines laid down by the University of Newcastle's Human Research Ethics Committee.

2.2. Apparatus

An IBM compatible computer and a WACOM 1212-R graphics tablet were used to record the horizontal and vertical position of a stylus as the participants wrote the pseudo-word "lanordam". The data were collected at a frequency of 206 Hz with a spatial resolution of 0.02 cm. The data collection and control program was written using the programming language OASIS (de Jong, Hulstijn, Kosterman, & Smits-Engelsman, 1996). The stylus was a modified WACOM inking pen, similar to a conventional ballpoint pen. The mono sound was generated through TEAC HF-11TV headphones attached to a soundblaster sound card controlled by the OASIS program. A data collection template consisting of a sheet of paper containing two columns of six horizontal lines was attached to the surface of the graphics tablet.

2.3. Procedure

The apparatus and methodology are similar to that used by Longstaff and Heath (2000). The participants practiced writing the pseudo-word lanordam several times to familiarize themselves with both the task and apparatus. The task was to write lanordam six times on a sheet of paper attached to the graphics tablet, under conditions of low and mild physical stress. The only guides the participants had for writing were two columns of six horizontal lines. In the low physical stress condition there was minimal additional sound. In the mild physical stress condition the participants wrote the words while listening to an annoying 65-dB, two-tone sound. The two tones (880, 1760 Hz) alternated at a rate of approximately 5 Hz. This level of sound is of similar intensity to a busy street. A mild intensity sound was chosen to ensure that the task was not unnecessarily stressful for the participants. The mono sound was presented through a set of headphones.

2.4. Preprocessing

The data were preprocessed and analyzed using the techniques reported in Longstaff and Heath (1999) (also used in Heath (2000) and Longstaff (2000)). These analysis techniques have been successfully used in several studies and have been shown to produce reliable results when applied to handwriting velocity profiles. The procedure (detailed below) involves taking the central stationary section of the velocity profiles from each word, concatenating them to produce long time series and finally, reducing the noise in the time series by using singular value decomposition.

An important concern when performing dynamical analyses of experimental time series is that they contain both a sufficiently large number of observations and minimum noise. It has been maintained that if the dimension of the system is 3, at least 1584 data points are needed (Nerenberg & Essex, 1990; Tsonis, 1992). The mean dimension estimates obtained by Longstaff and Heath (1999) were 3.24 for the horizontal velocity and 2.70 for the vertical velocity using a mean of 1920 data points. It was therefore concluded that 2000 data points would be adequate for the present study. In order to achieve time series of this length, several trials are concatenated.

Horizontal and vertical velocity time series were calculated using OASIS (de Jong et al., 1996) by dividing the pen movement distance by the time delay between two successive samples (in this case 1/206 s). To reduce variability due to measurement error the raw velocity signals were filtered using a seven point median filter (i.e. each point is replaced by the median out of a window of raw velocity values surrounding the current velocity sample). The tangential velocity used in the following analyses was calculated by using a Pythagorean transformation of the velocity in the horizontal and vertical directions.

The accuracy of the nonlinear dynamical analysis also depends on the data being stationary (i.e. the parameters of the time series, such as mean, variance etc., do not change over time). Particular care must be taken when several trials are concatenated to form larger files that this does not result in a nonstationary time series. This problem is minimized if these trials are samples from the same attractor. If nonstationarity is introduced when the data is chunked, the trials are most likely not from the same attractor, or some important parameter has changed. Longstaff and Heath (1999) demonstrated that properties of the attractor that generates handwriting (correlation dimension and Lyapunov exponents) are not significantly different when calculated from individual trials or concatenated trials from the same subject.

Additionally, these properties did not significantly change when either chunks or several concatenated chunks of standard nonlinear time series (e.g. Lorenz, Henon) were analyzed, further confirming the reliability and validity of this technique. In the present study, each raw data file contained many more than 500 data points. Variability at the beginning and end of a word is unrelated to the processes of interest. For example, this variability could include pauses when beginning to write the word and movements of the pen when the word has been completed but the pen is still on the page. In order to remove these sources of error and nonstationarity, only the middle 500 data points sampled on a trial were used in data analysis.

The static pen traces as well as the velocity time series were visually inspected for errors in the intended movements. Trials were rejected when the pseudo-word was not spelled correctly, when there were uncharacteristic pauses, incomplete words or any gross deviations from the general pattern used to write the pseudo-word. Trials were also rejected if they were written uncharacteristically fast or slow. This can be determined, for example, by noting the typical length of the resulting time series. If the trials are typically 1000 points long a trial with 500 or 2000 points will be rejected. While few trials needed to be rejected, two trials of the original six for each condition were discarded to ensure consistency. This resulted in four characteristic trials being analyzed for each participant in each condition. The data from these four trials were concatenated without further manipulation, resulting in time series that were 2000 data points in length. Finally, singular value decomposition (SVD) (see Appendix A) was applied to each concatenated time series to minimize experimental noise (Aubry, Holmes, & Lumley, 1988; Heath, 2000; Longstaff & Heath, 1999; Rapp, 1994; Sauer, 1992; Sprott & Rowlands, 1995). A typical example of a concatenated velocity time series can be seen in Fig. 1. Visual inspection suggests that the movement is stable over several trials, as was previously demonstrated by Longstaff and Heath (1999).

Since it had previously produced reliable results with this type of data (Heath, 2000; Longstaff, 2000; Longstaff & Heath, 1999), chaos data analyzer (CDA): the professional version (Sprott & Rowlands, 1995) was used to implement SVD and calculate the correlation dimensions (see Appendix A). Longstaff and Heath (1999) found that these dimensionality estimates were similar to those determined by other techniques such as the pointwise correlation dimension ($PD2_i$) [1] developed by Skinner and associates (Skinner, Goldberger, Mayer-Kress, & Ideker, 1990; Skinner et al., 1990; Skinner, Molnar, & Tomberg, 1994). $PD2_i$ is an alternative designed to be less sensitive to nonstationary sections within a time series.

A key step in the calculation of properties of a time series is the selection of the time delay. It is advisable that before a result is accepted, the analysis is performed on the time series using a number of different delays in order to determine the sensitivity of the original results to variations in this parameter. Longstaff and Heath (1999) found that the correlation dimensions calculated using several different delays

[1] The $PD2_i$ software was used under license from Totts Gap Software, 1430 Totts Gap Rd, Bangor, PA 18013, USA.

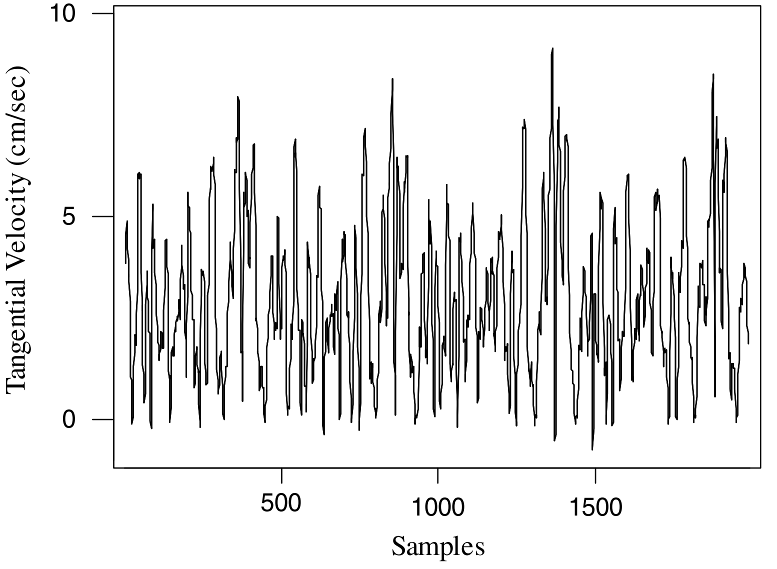

Fig. 1. Example of a tangential velocity time series created by concatenating data from four trials.

were comparable to the original results. Since the results calculated for the dimensional estimates were similar when using different time delays as well as using different techniques, the method of analysis used by Longstaff and Heath was employed in this study. Finally, as in the study by Longstaff and Heath, the NETLE analysis program was used to calculate the Lyapunov Spectra [2] (Gençay & Dechert, 1992; Kuan & Tung, 1995).

3. Results

3.1. Summary results of the dynamical analysis

Mean results of the dynamical analysis were first examined to confirm that the values were consistent with those found by Longstaff and Heath (1999), and therefore that the techniques and parameters used were appropriate. The correlation dimension was calculated for the concatenated tangential velocity time series of the participants' handwriting. The mean correlation dimension while writing in a relatively quiet environment was found to be 3.2 (SE = 0.31). When writing in a noisy environment the mean correlation dimension was found to be 3.38 (SE = 0.30). The mean dimensional estimates found by Longstaff and Heath ranged from 2.5 to 4.

[2] A detailed description of the theoretical basis and calculation of the Lyapunov spectrum is beyond the scope of this paper, although a basic description is contained in Appendix A. The reader should refer to Tsonis (1992), Wolf et al. (1985) or Gençay and Dechert (1992), for example.

The maximum Lyapunov exponent of the velocity time series was calculated for each participant. The mean of the maximum Lyapunov exponent (0.1293, SE $= 0.0104$, expressed in log base-e units) for the no additional sound condition was significantly positive, $t(21) = 12.40$, $p < 0.0001$. The mean sum of exponents (-0.9920, SE $= 0.0567$) was significantly negative, $t(22) = -17.23$, $p < 0.0001$. Similarly, the mean of the maximum Lyapunov exponent (0.11557, SE $= 0.00881$) for the additional sound condition was significantly positive, $t(22) = 13.12$, $p < 0.0001$ and the mean sum of exponents (-0.9691, SE $= 0.0608$) was significantly negative, $t(22) = -15.93$, $p < 0.0001$. In fact, the maximum Lyapunov exponent was positive and the sum of exponents was negative for all participants in both conditions. The mean maximum Lyapunov exponents found by Longstaff and Heath ranged from 0.106 to 0.145 and the mean sum of exponents ranged from −0.621 to −1.557. Since the values calculated are comparable to those found by Longstaff and Heath, it was concluded that the preprocessing techniques and analysis parameters were valid. With the reliability of these techniques confirmed, a more detailed analysis of the results was performed.

3.2. Analysis of the correlation dimension

The correlation dimension was calculated for the concatenated tangential velocity time series. Linear regression analysis was initially performed to determine if there was any relationship between the participants' age and the mean correlation dimension of their movement speed while writing. Since there was a relationship between these two variables, $R^2 - \text{adj} = 17.0\%$, $F(1,21) = 5.5$, $p = 0.029$, age was used as a covariate in an analysis of variance, resulting in a nonsignificant main effect for age, $F(1,20) = 0.050$, $p = 0.826$, and a nonsignificant interaction between age and sound condition. The mean correlation dimension for people with and without tremor writing the pseudo-word lanordam is shown in Fig. 2.

Fig. 2 indicates that the movements used by people with tremor to write words are generated by a lower dimensional process (mean $= 1.9$, SE $= 0.4$) than that used by people without tremor (mean $= 3.9$, SE $= 0.2$), $F(1,20) = 14.577$, $p = 0.001$. There was no significant difference between groups for the sound condition (sound: 3.2 SE $= 0.3$; no sound: 3.4, SE $= 0.3$), $F(1,20) = 0.108$, $p = 0.566$, nor was there any significant interaction of tremor group and noise condition on the correlation dimension.

3.3. Analysis of the largest Lyapunov exponents

The maximum Lyapunov exponent was calculated for the concatenated tangential velocity profiles. Linear regression analysis revealed no significant relationship between the age of the participant and the mean maximum Lyapunov exponent of their movement speed, $R^2(\text{adj}) = 6.8\%$, $F(1,21) = 2.62$, $p = 0.121$. Age was therefore not used as a covariate in the analysis of variance. The main effect of tremor group on the largest Lyapunov exponent, displayed in Fig. 3, shows that the tangential velocity is generated by a process with a larger maximum Lyapunov exponent for people

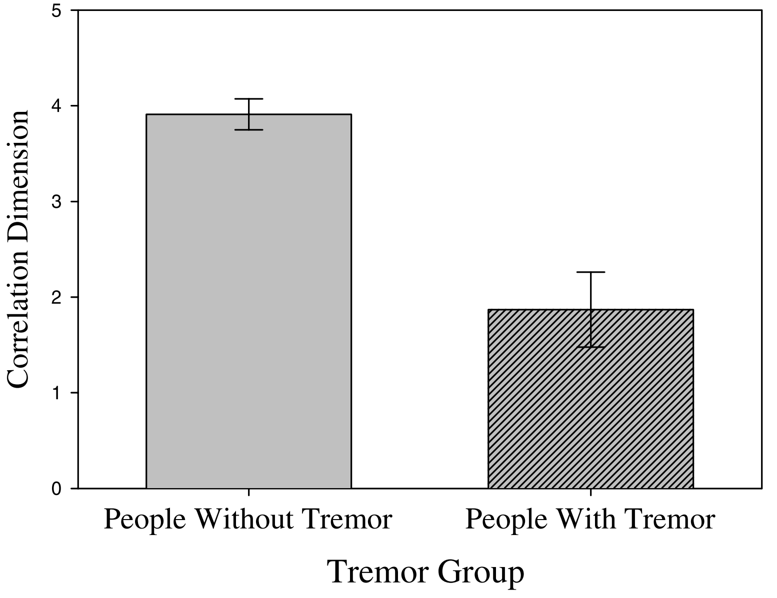

Fig. 2. Mean correlation dimension for people with and without tremor (vertical lines indicate standard errors).

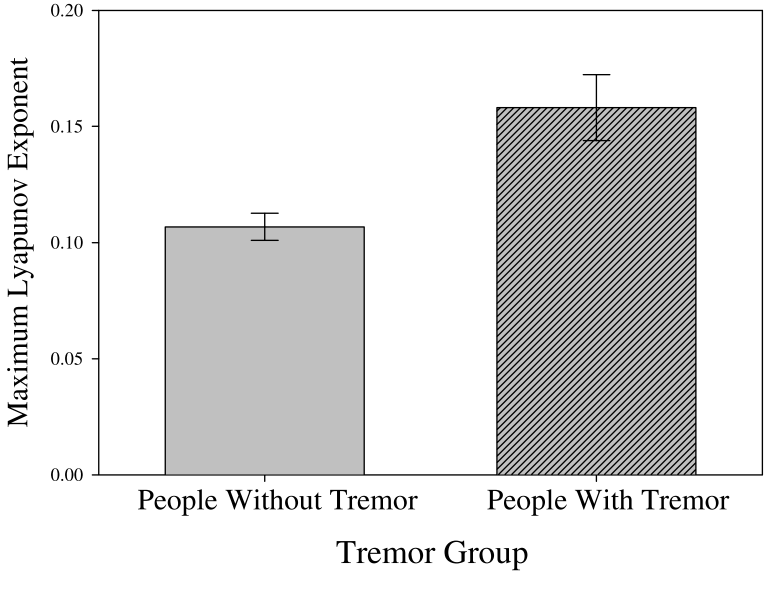

Fig. 3. Maximum Lyapunov exponent for the tangential velocity of handwriting movements for people with and without tremor (vertical lines indicate standard errors).

with tremor (mean = 0.158, SE = 0.014) than for people without tremor (mean = 0.107, SE = 0.006). There was no significant difference for the main effect of sound condition (sound: 1.116 SE = 0.009; no sound: 0.129, SE = 0.010), nor was there any significant interaction of tremor group and sound condition.

4. Discussion

The hypothesis that the correlation dimension of the tangential velocity of handwriting movements would be greater for healthy people than for people with tremor was supported. The results suggest that there is a difference of at least one dimension between the dynamical systems producing the tangential velocity of handwriting movements for those without tremor compared to those with tremor. This finding is consistent with the review paper by Newell and Vaillancourt (2001) which details a number of studies that show that disease is often accompanied by a reduction in dimensionality. This contrasts with research indicating that dimensionality reduces with learning a skill (Mitra et al., 1998), which suggests that reduced dimensionality is associated with improved control rather than reduced control. However, it is important to note that the goal of learning to control the system is not so much to reduce the dimensionality, but to find the optimal dimensionality of the system. As noted by Newell and Vaillancourt the dimension of the attractor dynamic of the motor output will change depending on the confluence of constraints in action. For example, Goodman et al. (2000) report that the number of active degrees of freedom required to capture the dynamics of a pendulum being oscillated at resonant frequency was 3, but this increased to 4 when the pendulum was oscillated at a nonresonant frequency. In the experimental paradigm of Mitra et al., the system started with too many active degrees of freedom, and through learning these were reduced to an optimal level. In a different task, it may be that the system begins with too few active degrees of freedom (e.g. the freezing of biomechanical df's discussed in Newell and Vaillancourt) which are increased to the optimal level through learning. Once the optimal level is found, a change from this will tend to result in a deterioration of performance. As noted above, disease processes have generally been found to result in reductions of dimensionality.

Previous research has demonstrated that healthy people respond to mild increases in physical stress or mental load by increasing muscle stiffness in order to maintain accuracy (Longstaff & Heath, 2000; van Gemmert & van Galen, 1997, 1998). This muscle stiffness is modulated by an increase in speed and/or by raising the axial pen pressure. Evidence has been presented for the argument that people with motor function degradation have less control over parameters associated with the reduction of unwanted movement variability. In particular, Longstaff and Heath (2000) found that people without tremor responded to a mildly stressful noisy environment by writing pseudo-words with greater pen pressure (and therefore greater muscle stiffness) than when in a relatively quiet environment. The pressure used by people with tremor either remained constant or was slightly lower. This resulted in more consistent handwriting (i.e. less variability) for people without tremor, but a tendency for the consistency of the handwriting of people with tremor to decrease.

The correlation dimension is a measure of the minimum number of control parameters, or active degrees of freedom, needed to fully describe the system. We argue that the difference in dimensionality between people who are healthy and those with tremor, at least in part, reflects the loss of control of degrees of freedom associated with an ability to minimize unwanted movement variability. While this assertion is speculative at this stage it is at least plausible that the reduction in active degrees of freedom is explained by a diminished ability to adaptively control muscle stiffness. As has already been noted the dimension of the motor output can change due to the particular constraints on the system. This could include competing tasks constraints such as the necessity to apply a constant force (e.g. increased pressure/stiffness) which might require an increase in the optimal active degrees of freedom, and the necessity to apply a sinusoidal varying force (i.e. to produce handwriting) which might require a decrease in the optimal active degrees of freedom. Further research will therefore be required before the hypothesized reduction in stiffness control can be confirmed.

The finding that the largest Lyapunov exponent was greater for people with tremor than for people without tremor was consistent with the hypothesis. In previous studies, the motor system of people with tremor was shown to contain more inherent variability than that of people without tremor (Longstaff, 2000; Longstaff & Heath, 2000). For example, Longstaff (2000) found that people with tremor traced mazes with significantly greater dysfluency. Dysfluency is a measure of how "smooth" a movement is during the execution of given task and relates to the number of velocity peaks (or velocity inversions) per distance traveled (or per second). It has been used in numerous studies as a measure of movement efficiency (Meulenbroek & van Galen, 1988; Mojet, 1991; Smits-Engelsman & van Galen, 1997; van den Heuvel, van Galen, Teulings, & van Gemmert, 1998; van Doorn & Keuss, 1991; Wright, Lindemann, & Dick, 1999).

The heightened unwanted variability in the motor system of people with tremor was more clearly demonstrated by Longstaff and Heath (2000) who found that the between trial coherency for the horizontal, vertical and tangential velocity profiles as well as for the axial pen pressure profiles, was greater for people without tremor. If the motor system of people with tremor contains more noisy variability, as shown by Longstaff and Heath, it is not surprising then that it would be also be less predictable. Since the largest Lyapunov exponent is a measure of the unpredictability of the system, any increase in its magnitude represents the generally higher level of unwanted noise variability that pervades the psychomotor system of people with motor skill degradation.

This increased unpredictability of the system's output implies that rather than thinking in terms of a pervasive level of "neuromotor noise" we should be thinking about the predictability of the system dynamics. In this context people with motor function degradation (e.g. from tremor, MS, Parkinson's Disease etc.) have a motor system with less predictable dynamics rather than simply having a "noisier" system. As there was no change in the correlation dimension or largest Lyapunov exponent when the participants wrote in a mildly stressful environment, these indices appear to measure a stable aspect of the psychomotor system. However, this needs to be confirmed with further empirical research. It could be that the stress was simply too mild to disrupt the fundamental dynamics of the system.

As hypothesized, the handwriting velocity profiles were found to be low dimensional. The hypothesis that the largest Lyapunov exponent would be positive and that the sum of the exponents would be negative was also supported. This compliments the findings reported by Longstaff and Heath (1999), and provides further support for the proposal that handwriting velocity profiles display nonlinear chaotic dynamics. These results are consistent with those detailed by Dooijes and Struzik (1994), who reported low dimensional estimates of handwriting traces, Kay (1988) who concluded that simple rhythmic finger movements are low dimensional and Mitra et al. (1997, 1998) who found simple rhythmic motor movements can be characterized as low dimensional nonlinear dynamical evolutions on a strange attractor. Furthermore, the results support the work by Akamatsu, Hannaford, and Stark (1986) who found that a muscle model based on the classic length tension curves could produce inherent oscillations during contraction that exhibited a positive largest Lyapunov exponent.

It could be argued that the low dimensional, nonlinear nature of the data is merely due to some peculiar feature of the actual word that was written, or possibly some artifact of the data collection apparatus. Perhaps it was due to the pre-processing techniques of concatenation of trials and SVD. These arguments can be easily discounted. In Longstaff and Heath (1999) the target character string was the pseudo-word 'madronal' and in the present study the letters were reversed to produce the pseudo-word lanordam. While the same letters were used in both words, there are sufficient differences in the way letters are joined in cursive writing for these words to require quite different movements, resulting from different letter combinations. The argument that the result is due to the apparatus or pre-processing technique can also be dismissed. If this were true, there would be no significant differences between the two groups in terms of the magnitude of either the correlation dimension or largest Lyapunov exponent.

This study employed some novel techniques in an attempt to further understand fine motor control. With a growing interest in measures such as dimensionality it is important not only to calculate raw values but also to try to understand changes in these parameters due to task constraints or population group. A critical aspect of this is to utilize knowledge gained from more conventional techniques. As such, the results of this study are interpreted within the context of what is already known about motor control in general as well as past findings with this population group. The results presented here indicate that the dimensionality of handwriting velocity profiles is lower for people with tremor than with people without tremor. It is speculated that this reflects a reduction in the ability to control movement parameters associated with minimization of unwanted variability. This leads to a movement outcome that is more variable (as found in a previous study) and less predictable, as measured by the largest Lyapunov exponent. Future research will further explore the possible causes for this reduction in dimensionality and increase in temporal unpredictability.

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Appendix A. Technical details of the dynamical systems analysis used in this study

A.1. Singular value decomposition

Singular value decomposition (SVD) derives orthogonal eigenfunctions from the original time series, each of which corresponds to one of a sequence of decreasing eigenvalues. Each eigenvalue represents the relative contribution of the corresponding eigenfunction towards fitting the original time series. A new time series based on the first few eigenfunctions weighted by their respective eigenvalues is computed. Since the additive noise is distributed evenly across the eigenfunctions the SVD method serves to increase the signal–noise ratio without altering the basic properties of the attractor.

A.2. Correlation dimension

The dimension of a system refers to the minimum number of scalar variables needed to model the dynamic process, or contain the attractor and hence provides a measure of the system's complexity. The dimension estimate in the present study is the correlation dimension, D_2, which is based on geometric properties of the attractor in phase space. D_2 is defined by Eq. (A.1) (Grassberger & Procaccia, 1983).

$$D_2 = \lim_{\varepsilon \to 0} \frac{\log C(\varepsilon)}{\log(\varepsilon)}, \tag{A.1}$$

where the correlation integral, $C(\varepsilon)$, is defined by

$$C(\varepsilon) = \lim_{N \to \infty} \frac{1}{N^2} \sum_{i,j=1}^{N} H\left(\varepsilon - \left|\mathbf{x}_i - \mathbf{x}_j\right|\right). \tag{A.2}$$

In Eq. (A.2) N is the total number of points, the ith point being represented by the m-dimensional vector, $\mathbf{x}_i$. $H(\cdot)$ is the Heaviside function which equals 1 when its argument is greater or equal to 0, and is equal to zero otherwise. Eq. (A.2) counts the number of pairs of points that are no greater than ε apart as a proportion of the total number of pairs of points in the data set. In practice, for any fixed value of embedding dimension, D_2 is estimated as the average slope in a plot of $\log c(\varepsilon)$ against $\log(\varepsilon)$ within a central almost linear scaling region.

A.3. Lyapunov spectra

Lyapunov spectra were calculated using NETLE (Gençay & Dechert, 1992; Kuan & Tung, 1995). This procedure uses a multilayer feed forward neural network to generate a nonlinear model of the experimental time series that is then used to estimate the Lyapunov spectrum. By definition, the Lyapunov exponents for a dynamical system measure the average rate of divergence or convergence of a typical trajectory (Gençay & Dechert, 1992). There are n Lyapunov exponents for an n-dimensional system. Using this definition, Gençay and Dechert (1992) state that all the Lyapunov exponents can be calculated using the Jacobian of the nonlinear function g (using the neural network) along a trajectory $\{x_t\}$. This function is estimated by the network and derives from differentiating the original nonlinear mapping in the embedding space. The technique used in NETLE involves estimating the nonlinear function g, which relates the next time series value to its previous values based on the reconstruction and then calculating the Lyapunov exponents of g using the definition in terms of the Jacobean functions.

Multilayer feedforward neural networks can asymptotically approximate a (differentiable) function and its derivatives to any degree of accuracy and with as few as a hundred observables. For the handwriting data, since the D_2 estimate was approximately 3, the embedding dimension chosen for NETLE was 7 (i.e. $2 \times D_2 + 1$). Lyapunov exponents were calculated using seven input units with the number of hidden units ranging from 1 to 14. The model that produced stable Lyapunov exponents was chosen and both the largest Lyapunov exponent and the sum of all Lyapunov exponents were calculated. The Schwartz information criterion (SIC), an index of the goodness of model fit, was used to select the appropriate number of hidden units. The Lyapunov spectrum generated from the network with the lowest SIC was used for further analysis.

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