Drawing in time: time-series analysis and human action

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ABSTRACT

We are concerned with analysing the temporal dynamics of simple skills, and whether such analysis can allow us to distinguish between different levels of ability. In order to do this, we focus on the task of drawing simple shapes. The challenge is to develop a means of collecting both force and movement data, and then describing these data in terms of time-series analysis. In this paper, we apply two methods for time-series analysis (*1/f* scaling and Approximate Entropy) to drawing. Ultimately, the goal of the work is to consider whether these measures allow us to differentiate ability in human performance. We show that it is possible to separate 'good' and 'poor' performers using these methods, and that this separation agrees with the self-identified ability of participants. If it is possible to provide ways of describing performance, then we can evaluate whether this is improving (as the result of rehabilitation or training) or whether it is deteriorating (as the result of injury or illness).

KEYWORDS

Human skills, time-series analysis, *1/f* scaling, entropy, drawing

Introduction

When we first learn to perform a new task (be it a toddler learning to walk, a grade-school child learning to play the violin, or a pensioner learning to wing-walk), there are many possible ways to perform the action, most of which are less than desirable and lead to unwanted outcomes. The task and the objects used impose constraints on performance (Newell, 1986) but we have flexibility over how to act inside these constraints. With practice, we discover ways of performing actions that require minimal effort and which permit high degrees of control. These correspond to minimum entropy (Hong, 2010). In other words, the 'system' (that is, the person performing an action with objects within the constraints of the task) self-organises, so that performance involves the most efficient combination of physical and cognitive effort. This means that 'expert' performers ought to have low levels of variability (because they will perform the action consistently). The implication of this statement is that ergonomics (and any subject involved in studying human performance) should have in its toolkit a set of methods which allow definition and measurement of entropy. A glance through ergonomics textbooks suggests that such a measure is scarce. One aim, therefore, in writing this paper is to present methods that allow entropy to be measured and to explore whether such methods provide useful information to the analyst. A reason why people might wish to apply such measures is for the objective evaluation of changes in performance, e.g., improvement due to rehabilitation or training, or deterioration due to illness, injury or task demands.

For ergonomics, entropy was a familiar measure of human activity in the 1950s (Crossman, 1953). It was typically used as a way of relating information theory to action (in terms of defining how a limited bandwidth channel could be used to control a movement). So, for example, Crossman's (1953) study involved people sorting cards under different conditions and he demonstrated how performance time varied according to task conditions. In this paper, our application of the concept is less to do with information channels for single actions and more to do with consistency of a signal over repeated trials. While entropy implies that low variability is desirable, it is paradoxical that too much consistency can be detrimental to performance because it reduces the potential to adapt in the face of changing task demands. So, the 'expert' balances variability and consistency to achieve 'optimum variability' (Goldberger, 1991). Across a series of studies, Bril shows how expert and novice practitioners differ in terms of their ability to respond to contextual demands (Biryukova et al., 2015; Bril et al., 2010, 2012). In this work, behaviour arises from the satisfaction of task specific constraints, which include the force to apply, the velocity or distance to move the tool to produce such force, and the angle of incidence for impacts between tool and material. The constraints define the functional parameters which need to be managed in order to achieve successful performance in the task. For instance, experts (flint-knappers and stone bead makers) seek to hold the functional parameter (kinetic energy) constant when using different types of hammer or material, while novices vary kinetic energy. In this paper, we take a much simpler task (drawing shapes) which people can self-identify as having high or low 'skill' in performing.

Drawing

From the preceding discussion, human movement requires the person to operate within constraints. In drawing (and handwriting) these constraints could involve the size and shape of drawing implements (and how easy these are to grasp and move), the contact between drawing implement and writing surface (and how easy it is to move smoothly), and the object to be drawn (and whether this requires changes in direction of movement). In terms of movement, there are systematic relationships between the velocity of the pen's tip and the geometry of its movement, such that the angular velocity of the pen's movement tends to be constant when radius of curvature changes (Viviani and Terzuolo, 1982), and follows a 2/3 Power Law (Lacquaniti et al., 1983). This suggests that, rather than the length of a line being the prime unit of control in drawing, shapes are decomposed into discrete 'units' and the transitions between units are managed. This means, for example, that people slow down when drawing tight curves. In their model of drawing, Lacquaniti et al. (1983) offer an elegant explanation of why this might occur as the result of the coupling of two independent oscillators. This implies that mathematical equations which reflect oscillator behaviour could be appropriate in the description of drawing. However, subsequent work suggests that the coupled oscillator model does not capture all aspects of drawing. For example, Wann et al. (1988) propose that people could produce behaviour that corresponds to the 2/3 Power Law through minimising jerk, i.e., by attempting to draw as smoothly as possible, and this can be described through mathematical analysis of the movement. In both cases, the velocity and pressure profiles (recorded through sensors on the drawing instrument or on the drawing surface) can be analysed to characterise changes in movement over time. As an example of a time-series, Figure 1 shows the trace of a participant drawing a triangle five times, without lifting the pen of the surface.

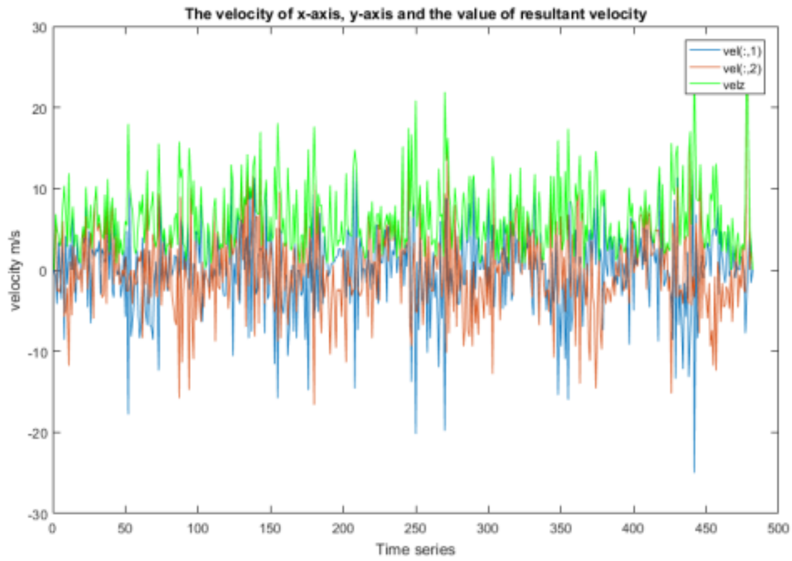


Figure 1: Example of velocity profile of drawing a simple shape

Knowing that the action (draw triangle) is repeated five times, we might be able to see some repeating pattern just by looking at the profile, but this does not provide sufficient evidence to tell whether the action is 'good' or 'poor'. We consider two approaches to the analysis of such time-series data.

Time-series analysis measures

Entropy

In Shannon entropy, used in information theory, H_s is given by:

$$H_s = -\sum_i p_i \log p_i \qquad [1])$$

where p_i is the probability of the i^{th} symbol being present in the system.

From equation [1]), H_s will be high if every state of the system has the same probability of occurrence. Entropy of a time series can be used to indicate consistency, i.e., in terms of repeating patterns within the time-series (Yentes, 2016). If the method cannot find many repeated patterns in data, then the signal could be called 'random' or 'chaotic'. Approximate entropy is a popular measure for this purpose, and is widely used in the medical domain, e.g, ion cardiology (Shin et al., 2006), respiration (Burioka et al., 2002), and biomechanics of gait (Georgoulis et al., 2006).

1/f scaling

1/f noise can be applied across different cognitive tasks to indicate a 'softly assembled' system focussing on interaction-dominant dynamics (component dynamics alter interactions) rather than component-dominant dynamics (behaviour arises from components, demarcated and assigned specific functions). There is compelling evidence that human activity exhibits long-term stability (or repeated patterns of variability) that indicate the existence of interaction-dominant systems (Kello et al., 2007).

Study One: 1/F scaling in scribbles and drawing simple geometric shapes

In this study, we asked participants to produce simple drawings and used *1/f* scaling to analyse their performance. The aim was to determine whether it is possible to distinguish 'good' and 'bad' performance in this activity, and whether such an objective distinction corresponds to the self-report of participants.

Participants

Seven participants (5 female, 2 male), all right handed, mean age 23 years, volunteered to take part in this study. Two participants self-identified as 'good drawers' and the others classed themselves as 'moderate' drawers.

Equipment and data analysis

Data were collected using a digitising tablet (Wacom INTUOS 4 XL). This is a large (487.7mm x 304.8mm) resistive surface on which participants draw with a purpose-built pen. The marks made on the surface are displayed on a display screen positioned in front of the surface. Pen movement and pressure were recorded and summarised using software called MovAlyzeR (NeuroScript, USA). Further analysis was conducted using MatLab (The MathWorks, USA).

Calculating 1/f scaling

Velocity and Pressure data were imported into MatLab and processed using the *pwelch* function to determine the signal power spectral density (PSD) with a Fast Fourier Transform (FFT) using a Hamming window length of 20 samples and an overlap of 10. After applying *pwelch*, the results were log transformed (log_e) for power and frequency, and a linear regression applied to the resulting scatterplot.

Procedure

The experimental design was approved by the Ethics Process in School of Engineering, University of Birmingham. Participants were asked to draw three different patterns:

1) scribble for 10 seconds;
2) rectangle (a four side shape with sharp angle); and
3) a square with a cross and a triangle on the top (which looked like a house).

Each drawing pattern was produced 10 times by each participant, and each pattern was to be performed without removing the pen from the surface (see figure 2). Prior to the data collection phase, each participant was given a brief explanation of the experiment and allowed to practice using the pen to draw shapes and scribble on the tablet. Next, participants were asked to produce three examples of each of the drawing actions. If they had problems in drawing the shapes without lifting the pen, this was discussed and alternative ways of performing the action suggested. Once the participant was confident that the shapes could be drawn without difficulty, the data collection began. Data (velocity, acceleration, pen pressure) were collected at a rate of 100Hz.

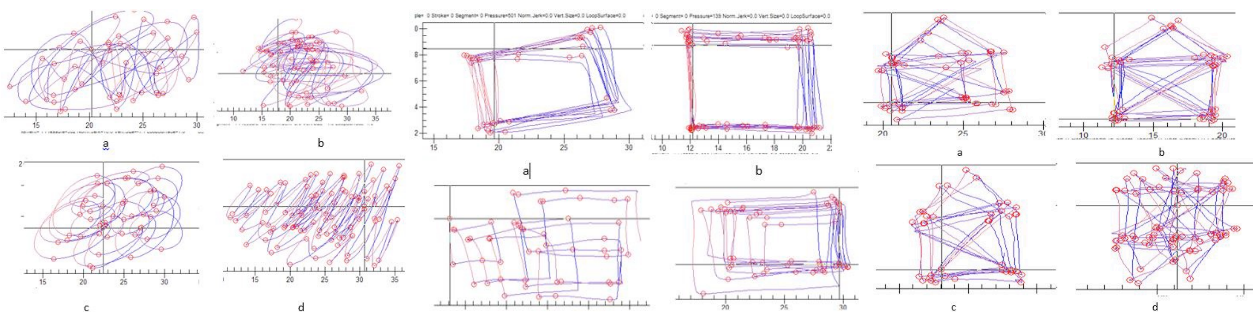


Figure 2: Examples of Drawings (scribble, rectangle, 'house')

Results

The summary of velocity (m/s) data for each participant is shown in Table 1.

Table 1: Summary of Velocity Data

		Participant						
Shape	V_Mean	1	2	3	4	5	6	7
Scribble	36.9	27.7	61.1	25.2	44.1	50.5	39.3	10.3
Rectangle	14.3	10.2	12.1	8.1	21.1	15.8	21.5	11.5
'Square and cross'	7.9	6.3	8.7	10.2	3.2	7.5	10.1	9.1
Mean		14.7	27.3	14.5	22.8	24.5	23.7	10.3

From Table 1, one can see that participants had higher velocity when scribbling than when drawing the 'house', with the square between these two. Participant 7 is an interesting case, in that her results tended to have similar (quite slow) velocity on all shapes.

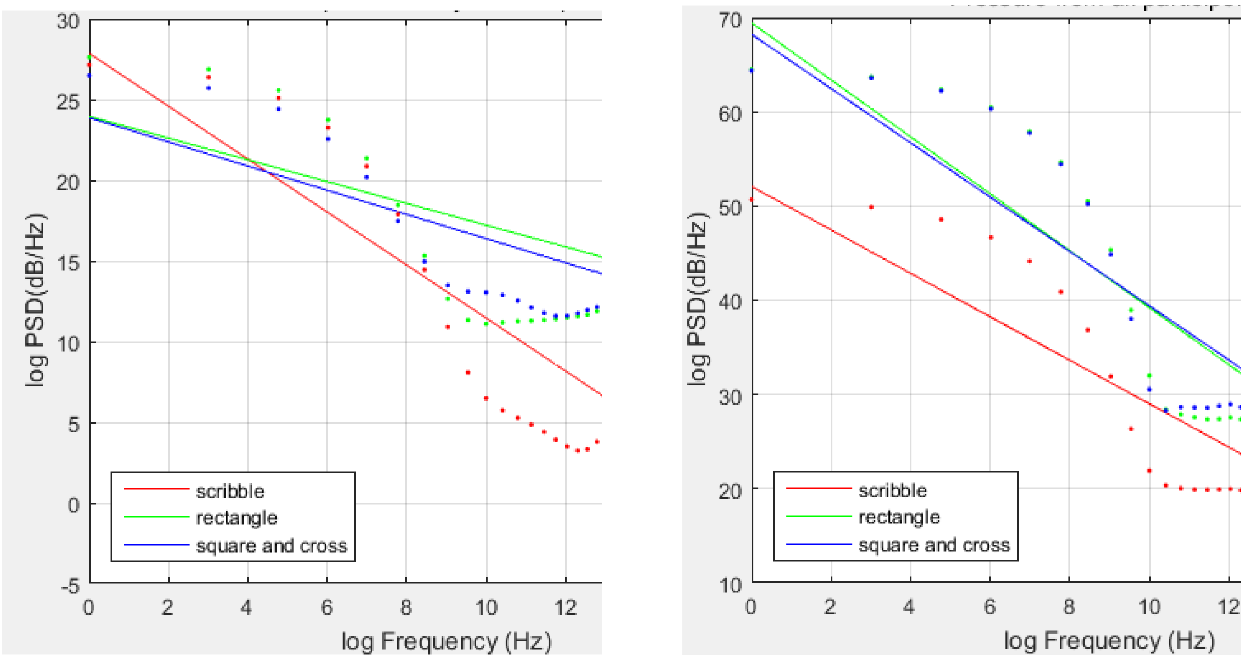


Figure 3: Summary analysis of velocity (left) and pressure (right) for the different shapes

In *1/f* scaling, the slope of the line is indicative of the stability of the system that produced the data. So, a highly stable 'system' would have a steep slope, and a highly variable system would have a shallow slope. We can see, from the graphs in Figure 3, that the 'scribble' has a steep velocity slope and a similar pressure slope to the other shapes.

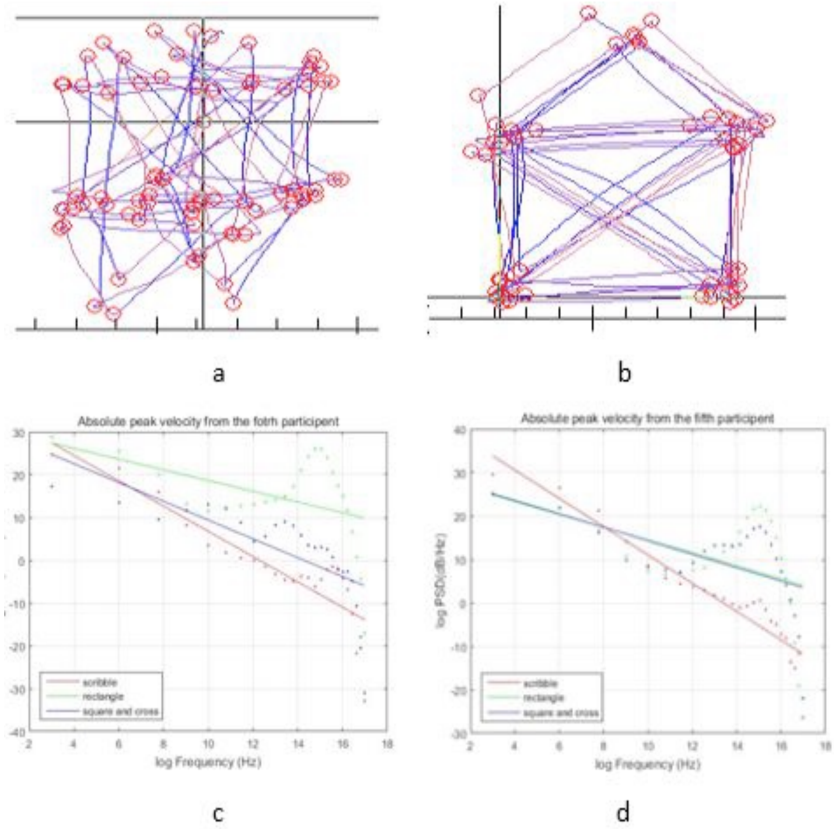
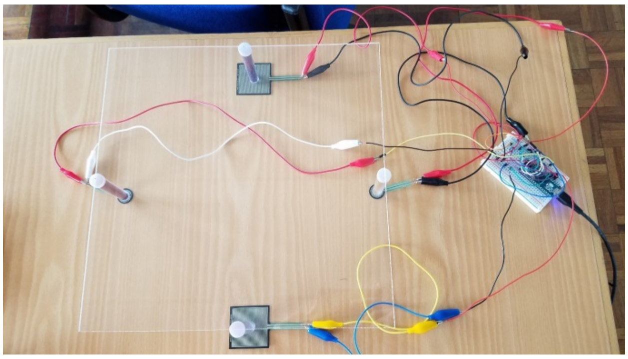


Figure 4: Comparison of ‘best’ and ‘worst’ drawer in this study

Figure 4 shows the performance on the ‘square and cross’ task of two participants who, in their own opinion found the task ‘hard’ (a, c) or ‘easy’ (b, d). While there is not much difference in the ‘scribble’ slope, there is a clear difference in the slopes for the rectangle and ‘square and cross’. Comparing graphs (c) and (d), the rectangle for the participant who found the task ‘hard’ (c) is relatively flat, implying that there was less control in its production, while the slope for the ‘square and cross’ is a little steeper, implying more control. The slopes of the lines can be quantitatively compared using their regression coefficients (R^2), which are around -3 for the scribble, -1.23 and -2.13 for the rectangle; -2.5 and -2 for the ‘square and cross’. This implies that there was little variability in the production of the scribble. People would hold the pen and move it at the same velocity and with little effort to alter this movement. In contrast, the shapes which required change of velocity at angles show more variability in velocity. This is, as one would expect, a reflection of the control demands of the task.

Study Two: Approximate Entropy

Rather than drawing on a tablet, we wanted to record drawing on paper. Obviously, one cannot put paper on a capacitive tablet surface and use a normal pen, so we decided to design and build our own surface (using Force Sensitive Resistors and an Arduino microprocessor).



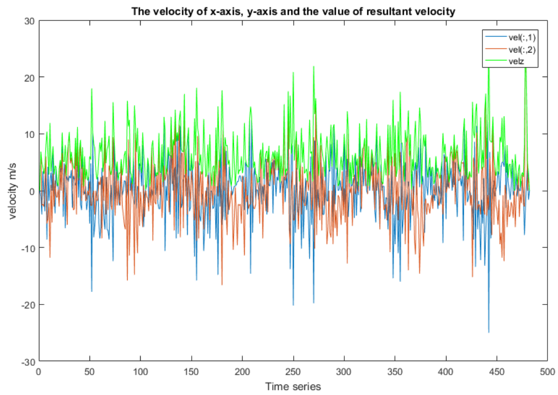


Figure 5: Drawing board and Velocity trace of one participant drawing five triangles

Calculating Approximate Entropy

Entropy involves dividing a waveform into sections, and then comparing each section to all other sections. If adjacent sections match, then entropy is low, and the waveform (at that point) is stable. To calculate approximate entropy, we need: the length N of input time series, the length m of a vector, and the tolerance radius r. Selection of these values is explained by Yentes (2016). As an example, a time series with $N = 6$ could be $\{x1, x2, x3, x4, x5, x6\}$. Assuming a vector length, m, = 2, we divide the time series into 5 (N-m+1) x 2 digit vectors: $\{x1, x2\}$, $\{x2, x3\}$, $\{x3, x4\}$, $\{x4, x5\}$ and $\{x5, x6\}$. If we set radius $r = 1$, then the first 2 digit vector, $\{x1, x2\}$, can be compared with others in the 5 vector series, assuming ($x1$-r, $x1$+r). If there is a match, then it is counted and recorded as the conditional probability (i.e., match / N). This is repeated for all 2 digit vectors. Next, let m = m+1, and repeat the process. The conditional probabilities are converted to natural logs, and the sum of scores for m and m+1 calculated. The approximate entropy is calculated as log score m – log score m+1. The range of the values of approximate entropy is from 0 to 2, 0 indicates no entropy or a perfectly repeatable series (sine wave); 2 indicates a random series (white noise). Thus, lower values indicate greater stability in the data; higher values indicate more variability.

Results

From table 2, drawing a triangle using the left hand has highest entropy. This suggests that performance is more variable (for some of the participants) which, in turn, suggests that the control required in performing this action is the most difficult. This could be due to the difficulty a right-handed person has in manoeuvring the pen in the various turns required for the triangle.

Table 2: Approximate Entropy averaged for each participant and each shape

Participant	Mean	Circle_L	Circle_R		Triangle_L	Triangle_R
1	0.65	0.76	0.51		0.69	0.65
2	0.38	0.34	0.36		0.41	0.42
3	0.57	0.55	0.40		0.71	0.61
4	0.43	0.42	0.40		0.49	0.39
5	0.56	0.63	0.42		0.55	0.65
Mean		0.54	0.42		0.57	0.54

By contrast, drawing a circle using the right-hand had the lowest entropy and suggests smooth, easy performance. Figure 6 shows the shapes that were recorded from the drawing surface.

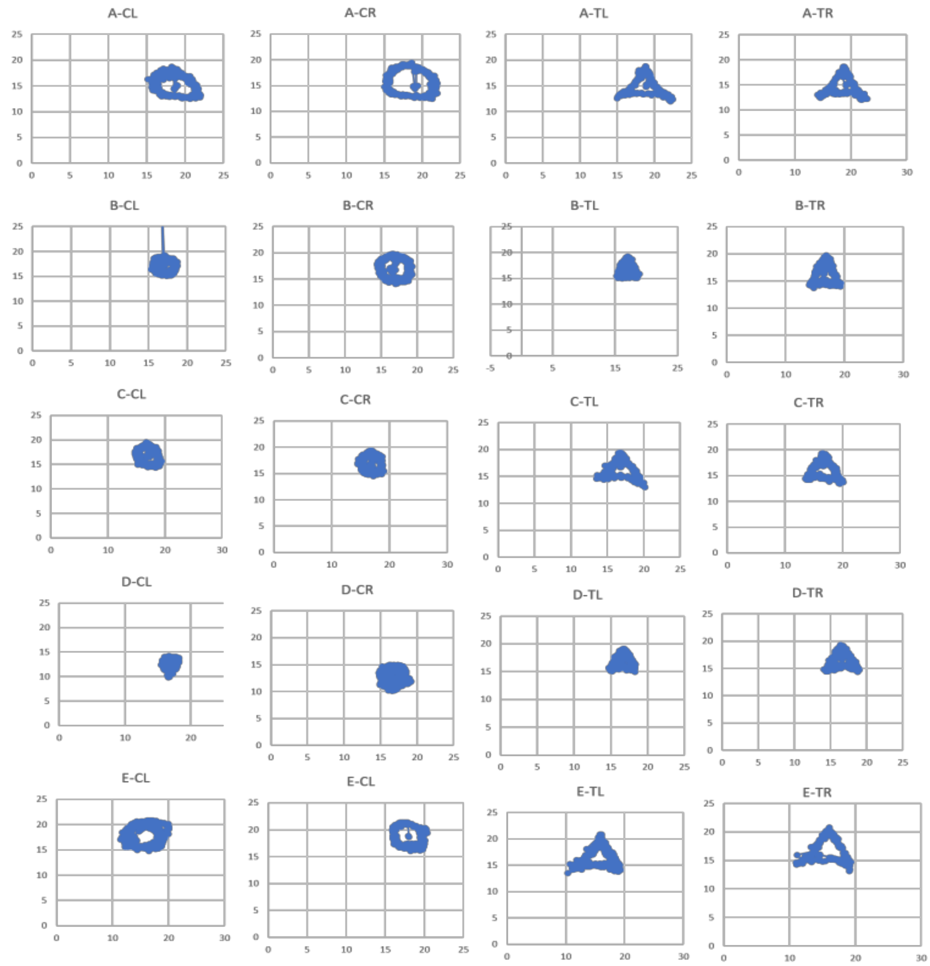


Figure 6: Recordings of shapes drawn by participants. Each row contains the lines drawn by one participant. The shapes are: Circle drawn with left hand; circle drawn with right hand; triangle drawn with left hand; triangle drawn with right hand.

From Figure 6, one can visually identify some set of shapes as being more symmetrical or 'tidy' than others. These correspond, to some extent, with self-identified drawing abilities of the participants. So, participants 2 and 4 felt that they were 'good' at drawing. Considering the entropy scores in Table 2, one can see that these participants tended to have lower scores than the others.

Discussion

Our aim in writing this paper was to present two methods for time-series analysis which can be applied to human movement. We have used drawing shapes as the candidate task and asked whether it was possible to differentiate, on the basis of repeated performance of a drawing task, good and poor performance. Comparing the results suggests that there is potential for such an approach: there are differences between participants, and these differences seem to reflect the visual appearance of the drawn shapes and the self-identified drawing abilities of participants. Generalising from this study, it is proposed that understanding variability in human movement can not only provide insight into variation in 'skill' but can also be used as a means of quantifying differences in performance, say due to injury or debilitation. In other words, time-series analysis could be a useful means of analysing simple repetitive actions that an occupational therapist might ask a stroke patient to perform. Calculating the entropy or the slope of a *1/f* plot can be used to compare performance across different trials in order to assess improvement or deterioration objectively.

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