Fractal Modeling of Human Psychomotor Skills Acquisition Process

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Abstract. Existing research on human skills acquisition studies has shown that learning follows a non-linear pattern, but the exact form remains unknown due to the limitation of traditional experimental methods and lack of systematic modeling of tasks. We applied a non-linear fractal analysis on the time series data produced by human subjects on target-tracking motor learning tasks. Tracking of a non-fractal sinusoid-cosinusoid signal was used as the platform. Our preliminary results suggest that fractal models may prove effective in investigating details of the human learning process.

Keywords: Fractal analysis, human learning, skill acquisition.

1 Introduction

Human psychomotor learning refers to physical or manual skills development, such as skilled performance of a musical instrument, driving a car or flying an airplane; this domain includes physical movement, coordination and use of motor-skill areas. Empirical research on human psychomotor learning can be traced back to the early 19th century when people tried to understand and examine different body movements related to their jobs [18]. Post World War II, with more studies from different disciplines on human motor learning, the development of machine complexity and the emergence of various theories of learning, psychomotor learning studies have become more systematic and achieved a more solid theoretical basis. Many learning theories such as Fitt's law [8] [9], memory drum theory [11], close-loop theory [1] and schema theory [17] [18] have been developed to try to explain the human learning mechanism of motor tasks, and continue to be developed [18] [19]. Many models and theories were developed to attempt to study human motor skills, in terms of its capabilities and limitations [1] [8] [9] [11] [17] [18].

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Human motor skills can be measured through performance outcome and via subjective feedback or self-report. Outcome performance measures (e.g. movement time, response time, movement accuracy) were used most of time [18]. Of all the performance measures, one particular interest is how to measure the learning process of human psychomotor skills. Traditional studies in this domain applied an empirical approach, for example, researchers attempted to show the effect of discrete levels of some independent variables on the learning. These studies were mostly non-analytic [7] and cannot reveal the continuity effect of this variable, thus the overall learning process is unknown. Most studies collect learning data in discrete stages, i.e., learning data for different trials, thus the data collected did not show too much of the continuity in learning time series. Furthermore, many studies did not take prior learning amount or experience into account – learning was administered for a fixed number of trials for all subjects and data collected tend to be from immediately after a limited learning exercise. Another shortcoming is that they only provide “crude” measure by giving one global mean value [6] [14].

Another approach is to use a performance curve fitting technique [18] to provide a more comprehensive measure of learning and a clearer picture of the learning process. It has been found that human learning follows a nonlinear pattern. That is, the improvement from practice is rapid in the beginning but decreases as the learner becomes more skilled. Newell and Rosenbloom’s influential paper [15], titled “Mechanisms of Skill Acquisition and the Law of Practice”, studied the relationship between response time and practice trials. They investigated diverse ranges of tasks, and found that the fitting is more of a power function rather than an exponential form [10]. The performance curve was claimed to be a major improvement for learning process estimates [6]. Using this method, the curve equation provides estimates for rate of initial level of performance, rate of improvement, and the asymptotic level of performance for a particular group (e.g., type of learning).

However, there are several drawbacks with curve fitting and traditional regression models. Just as Schmidt and Lee [18] pointed out, since the curve is built on the mean value of group performance data, it is “insensitive to the differences among individuals that arise as a function of practice”. That is to say, the performance curve cancels out some of the difference among people for a given trial; this difference may be important to show the true learning improvement trend with practice. The second limitation is that the performance curve also obscures the within-subject variability by averaging the performance over a large group of people. So the generalization and applicability of such a curve is limited, since the behavior of group learning hides many important factors. Thus we may predict that a learning process has achieved its steady state by looking at its group mean asymptote, but in fact, the variability for this time point is still large. Learning curves for other types of learning have found similar limitations [22].

From the literature in psychomotor skill learning studies, it can be concluded that the learning mechanism is still poorly understood due to lack of understanding of the nature of task and the dynamic nature of the learning process thus making it difficult to systematically model the learning process. Existing methodologies in psychomotor skill research imposes limitations on modeling capabilities. No theoretical models have been established from these studies to enable prediction of learning efficiency and transfer. In order to find the true mechanism behind human learning and effects of tasks on human learning of psychomotor skills, we need to go beyond these limits. Traditional research methods are of little use for investigation of this process. It is therefore essential to include well developed mathematical techniques and models into the picture. In our study, we adopted a spatiotemporal fractal analysis to investigate the nature of the human learning process.

2 Fractal Analysis of Non-stationary Time Series Data

2.1 Fractal Nature of Human Learning

The mathematical theory of fractals brings to us a new set of ideas and thus fresh ways of looking at nature, human interactions with the nature, and the learning process. With this viewpoint come new tools to analyze experimental data and interpret the results. The essential characteristic of fractals is that as finer details are revealed at higher magnifications the form of the details is similar to the whole: there is self-similarity. A simple example of a fractal object is a fern, shown in Figure 1. The number of branches increases in a **power law** fashion with each subsequent generation from the first mother branch. If one were to zoom in on a small part, the zoomed in object would resemble the whole. Such scaling and fractal behavior is ubiquitous in the universe. In human physiology, fractal structure has been studied in numerous contexts including the arterial branching system in the kidney, the alimentary tract, the bile duct system, in nerves and muscles such as the heart, and finally the convoluted surface of the brain [2].

Fig. 1. Fractal fern

Since fractal behavior is so universal in nature, it is perhaps not surprising that it is found as well in studies of memory and the process of learning. In an associative memory, the accuracy of identifying an input with the stored memory traces undergoes a transition from very good to very poor, as the number of stored memories increases. In other words, the process of memory also seems to follow behavior consistent with the fractal picture. Memory is obviously a crucial aspect of the learning process [18], so it would appear that fractal ideas are also helpful in understanding the way in which human beings learn. This leads us to consider that human skill acquisition processes influenced by the external task variations will show fractal patterns as well. No literature can found in applying fractal analysis on human learning process studies.

2.2 Detrended Fluctuation Analysis

Novel ideas from statistical physics led to the development of the detrended fluctuation analysis (DFA) [16]. The method is a modified root mean squared analysis of a random walk designed specifically to be able to deal with nonstationarities in nonlinear data, and is among the most robust of statistical techniques designed to detect long-range correlations in time series [3] [4] [20]. DFA has been shown to be robust to the presence of trends [12] and nonstationary time series [5] [13] [21].

The methodology begins by removing the mean, $\overline{B}$, from the time series, *B(t)*, and then integrating

$$y(k) = \sum_{t=1}^{k} [B(t) - \overline{B}] \tag{1}$$

The new time-series is then divided into boxes of equal length, *n*. The trend, represented by a least-squares fit to the data, is removed from each box; the trend is usually a linear, quadratic, or cubic function. Box *n* has its abscissa denoted by $y_n(k)$. Next the trend is removed from the integrated time series, *y(k)*, by subtracting the local trend, $y_n(k)$, in each box.

For a given box size *n*, the characteristic size of the fluctuations, denoted by *F(n)*, is then calculated as the root mean squared deviation between *y(k)* and its trend in each box

$$F(n) = \sqrt{\frac{1}{N} \sum_{k=1}^{N} [y(k) - y_n(k)]^2} \tag{2}$$

This calculation is performed over all time scales (box sizes). A power-law scaling between *F(n)* and *n* indicates the presence of scaling

$$F(n) \propto n^{\alpha} \tag{3}$$

where the parameter α is a scaling exponent.

We will apply DFA to our psychomotor experimental data, whose acquisition is described below, in order to explore the possible presence of fractal behaviors.

3 Experimental Method

3.1 Apparatus

The study used a Wacom Graphire4® USB Tablet and pen as the tracking devices. The tracking software was developed by using MATLAB 7. The following Figure 2 illustrates the hardware used and interface of the software.

In this testbed, a square box (target) moves across the screen at a predetermined constant speed following a sinusoid-cosinusoid signal path, $Y_m(r,t)$ The subject is required to use the pen on the Tablet to drive a cross (cursor) to follow this box, and to stay within the box as much as possible. We thus have a spatiotemporal tracking signal, *Y(r,t)*, from the subject. Performance data (the location of the target, and

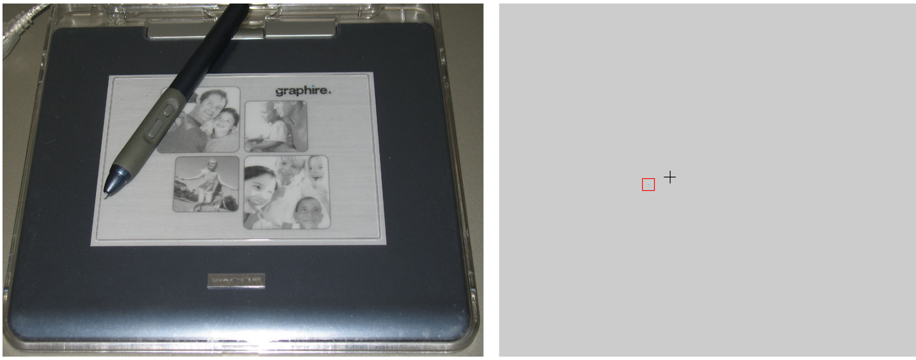

Fig. 2. Experiment testbed: Wacom Tablet and tracking pen (left), tracking software screenshot (right)

location of the cursor) was recorded five times every one second. The tracking performance was assessed by calculating the fluctuation from the actual target location and subject cursor location, $D=Y(t)-Y_m(t)$. Following this we extracted the temporal fractal scaling exponent from the vector fluctuation function. We have no clear *a priori* reason to expect that such a fractal scaling even exists. However, the fractal nature of some human physiology and neurophysiology leads us to suspect this possibility.

3.2 Procedure

We recruited college students to participate in this study. In this initial study we present results from just one subject in order to demonstrate our experimental and analysis techniques. To eliminate the possibility that efficiency will be influenced by memory, the human subject was not notified the path goal *a priori*. Upon arrival to the test location, subjects are briefed on the study objectives and procedures, and sign an informed consent form. They then are instructed to use the stylus and tablet to track the target and allowed access to the stylus and tablet a short time before the experimental task to become familiar with the experiment architecture.

Each session of the task takes 20 minutes, every two minutes of tracking followed by a 1-2 minute break to avoid subject fatigue. Each subject performs two sessions, one using primary hand, and one using the secondary hand (i.e., if he/she is a right handed person, then the right hand is primary, the other hand is the secondary hand). The sequence of primary and secondary hand were randomized to counterbalance the learning transfer effect between two hands.

4 Results

The detailed analysis of tracking data for one subject is now considered. The results for left hand tracking are shown. Figure 3 (top left) shows the fluctuation data, computed by subtracting the tracking from the target sinusoidal values. The subject generally performed tracking quite well. This is clear by the majority of data points clustering around the origin, which corresponds to zero fluctuation error (perfect tracking). There are a few significant deviations that occurred at least once in the positive Y-direction (up direction) and in both the positive and negative X-directions. The actually tracking data in XY are shown in the top right plot, and the fluctuations are shown plotted as a function of time in the lower left plot. Red corresponds to the X-fluctuations, and blue to the Y-fluctuations. It is clear from this plot that the amplitude of the fluctuations is much smaller in the Y-direction, demonstrating more accurate tracking in this direction; this is presumably due to the use of different muscle groups with finer psychomotor control for up/down motion than left/right motion.

Figure 4 shows the probability distribution functions for the X and Y motion. To test whether the data are normal we used a standard Lilliefors' composite goodness-of-fit test. The Lilliefors goodness-of-fit test considers whether the data in the vector D came from an unspecified normal distribution, and returns the result of the test in H. H=0 indicates that the hypothesis that data are normally distributed cannot be rejected at the 5% significance level. For our subject we found H=1; this indicates that the null hypothesis can be rejected at the 5% level. We found that the t location-scale distribution was an excellent fit to the empirical distributions. The t location-scale distribution is useful for modeling data whose distributions have heavier tails than the normal distributions.

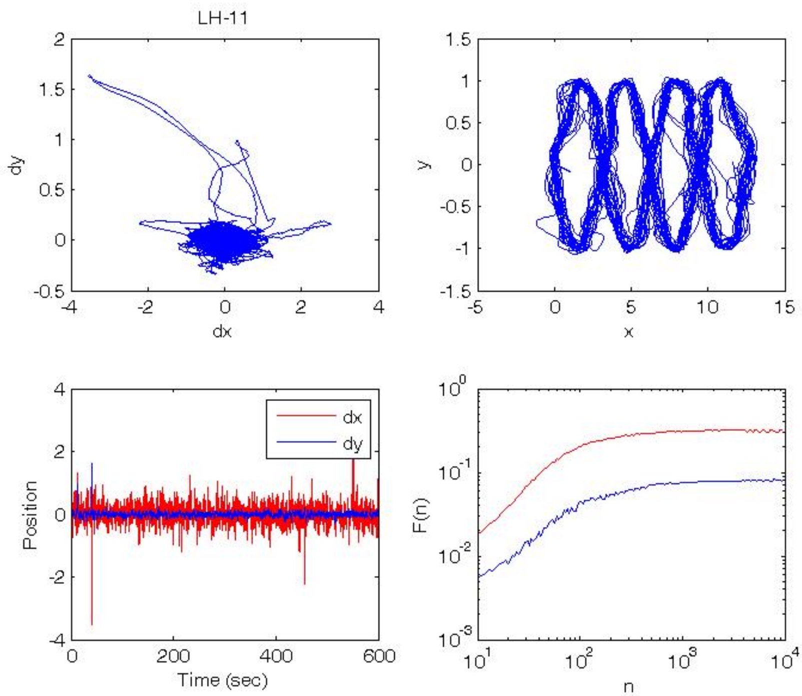

Fig. 3. Left hand human tracking data

The t location-scale distribution has the density function

$$\frac{\Gamma(\frac{\nu+1}{2})}{\sigma\sqrt{\nu\pi}\Gamma(\frac{\nu}{2})}\left[\frac{\nu+(\frac{x-\mu}{\sigma})^2}{\nu}\right]^{-(\frac{\nu+1}{2})} \tag{4}$$

with location parameter μ, scale parameter σ, and shape parameter ν. for the fluctuations in the X-direction, we found $\mu = 0.0011 \pm 0.0001; \sigma = 0.253 \pm 0.001; \nu = 5.7 \pm 0.2$ and for the Y-direction $\mu = -0.0062 \pm 0.0003; \sigma = 0.0511 \pm 0.003; \nu = 4.6 \pm 0.1$. The large scale function for the X-fluctuations indicates the much broader range of possible fluctuations in this direction.

Finally we turn to fractal analysis of the perturbations shown in the bottom left plot of Figure 3, which shows the results from DFA. The fractal fluctuation function *F(n)* as a function of the temporal scale size is shown in the lower right plot of Figure 3. A power law trend is apparent for the small scales for both fluctuations in the X- and Y-directions. We fit these between the scales of n=10 to 100. The fractal scaling exponent for the X-direction was $\alpha = 1.22 \pm 0.01$ and for the Y-direction $\alpha = 0.96 \pm 0.03$. The linear correlation coefficients of the raw data are r_x=0.999 and r_y=0.987.

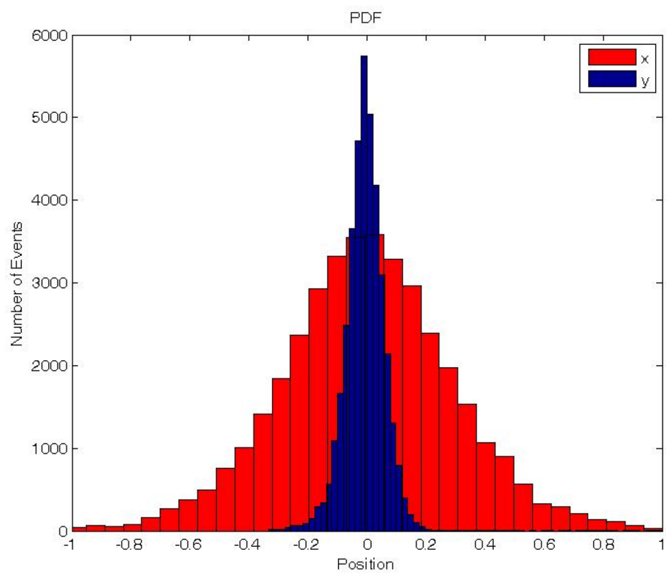

Fig. 4. Probability distribution functions for the X and Y motion fluctuations

5 Discussions and Conclusions

This study applied an innovative mathematical approach in human psychomotor skills learning studies. It is an advance in that a continuum of 'activity' levels can be modeled via fractal mathematical techniques; this advance can be seen both in model used and in terms of task manipulation itself.

In this study, we used DFA to examine the temporal variations of the nonlinear complexity of the psychomotor learning task previously described. We probed the existence of correlated behavior over the entire experimental time series. From our results, DFA analysis on all data demonstrated that the human psychomotor task learning, at time scales up to about two seconds (100 data points), is fractal – strong evidence is the existence of clear power laws for the fluctuations F(n).

This study helped to advance knowledge in the field of human psychomotor skills learning in terms of introduction of new ideas regarding the possible role of fractal processes in learning process efficiency and learning transfer. At this time, understanding of the development of human psychomotor skills is still extremely limited. This is largely due to the dynamic nature and variety of the task, lack of in-depth understanding and controllability of the task itself and the difficulty of measure of stochastic learning process by traditional methodologies. By using a specified task motion model (such as the sinusoid-cosinusoid signal model we applied here), this study provides a well defined structure for researchers to systematically quantify and control the task noise levels thus making the prediction more meaningful. The fractal learning model developed from this study will provide an innovative approach to integrating external causes of the human behavior into the picture, enabling researchers to obtain a more comprehensive picture of the problem. The model will provide detailed information regarding the nature of development of psychomotor skills.

Our study also applied a novel approach in data capturing in the behavior science domain. As stated in previous sections, traditional learning studies utilized discrete experiment data (i.e., different trials performance); this type of data cannot tell too much about the continuity of the learning process and more importantly, it limits the scope of analytical models that can be applied towards these data. The time series data generated from this study will enable many new statistical models to be applied on these data, so a more in-depth analysis can be performed.

To summarize, we have presented a new paradigm for the roots of psychomotor learning. In this paper we have presented only very preliminary experimental evidence in support of this view. We found a fractal scaling behavior was obtained for small temporal scales. These intriguing results will be further elucidated by further experiments on statistically significant samples, such as including a larger sample of human subjects and incorporation of different motion noises into the task such as Brownian motion. We believe this type of research will be of particular value to the field of human motor learning and training, to open a new window for studying human learning behavior within a specific human motor task context, and can provide great insights to those who train people on different psychomotor skills, and provide a valid prediction model on how to design a variable task to maximize the learning efficiency.

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