

1/f-type fluctuation in human visuomotor transformation

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In the absence of vision of the limb, movements toward a visual target exhibit substantial errors which are considered to originate mainly in the visuomotor transformation process. To determine the time-dependent property of human visuomotor transformation, we investigated the error sequences in movements toward visual target using scaling analyses. When subjects could see their controlling limb, the error sequences could not be distinguished

from a random sequence. On the other hand, when the controlling limb was invisible, the error sequences were not random in order, but exhibited 1/f-type time correlation. This finding that the variation in human visuomotor transformation shows 1/f-type fluctuation provides a significant index for mathematical modeling and system identification in human visuomotor control. *NeuroReport* 15:1133–1136 © 2004 Lippincott Williams & Wilkins.

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INTRODUCTION

In goal-directed movements such as reaching or pointing, the location of the controlling limb endpoint, such as the fingertip, must be finally matched with the external target location. The location of targets is usually defined in a visual frame, whereas that of the controlling limb endpoint is defined by the orientations of the limb segments. Transformation of the external target coordinate specified in visual space into motor and kinesthetic coordinates is a necessary step in controlling goal-directed movements [1–4]. To investigate human visuomotor transformation, psychophysical studies have analyzed the errors in visual-target directed movements. Soechting and Flanders [1] demonstrated that when subjects pointed to remembered visual targets in a dark room, the amplitude of constant errors could reach ≈ 15 cm. However, the errors were much smaller when subjects used a long pointer to localize the remembered visual target or when they reproduced the kinesthetically presented position of their finger. That is, the substantial errors in pointing to the remembered target were not due to poor visual memory or inaccurate kinesthetic perception but were the result of erroneous transformation from visual representation of the target location into kinematic representation of limb movements.

Movement errors without visual feedback of the moving limb have been widely analyzed to elucidate the principle for human sensorimotor transformation or integration [2–4]. However, the preceding studies went no further than using static statistical measures such as mean, s.d. and correlation

coefficient, which ignore the order of data sets. In other words, the preceding studies paid no attention to a possible time-dependent property for the error sequence. In the last decade, modern scaling analyses have shown that the variation sequences in some types of human motor behavior are not random in order but have long-range time correlations with a fractal (scaling-free) characteristic [5–9]. In this study, we used scaling analyses to reveal the trial-by-trial sequential property of the error in movements toward visual target to provide a novel viewpoint and insight into human visuomotor transformation.

MATERIALS AND METHODS

Subjects: Eight right-handed, healthy male subjects (age 30.3 ± 4.9 years) participated in this study after giving informed consent. This study was approved by the ethics committee of the National Rehabilitation Center for Persons with Disabilities.

Apparatus and data acquisition: Each subject was seated with his head immobilized by a chin holder and a forehead strap. The subject's right forearm and fingertip were strapped to a lightweight manipulandum set at shoulder height (Fig. 1a). The subject's forearm could rotate smoothly in a horizontal plane. The friction around the rotation could be ignored. A potentiometer was attached to the axis of rotation of the manipulandum to record its angular position. The recorded data were digitized at 1000 Hz.

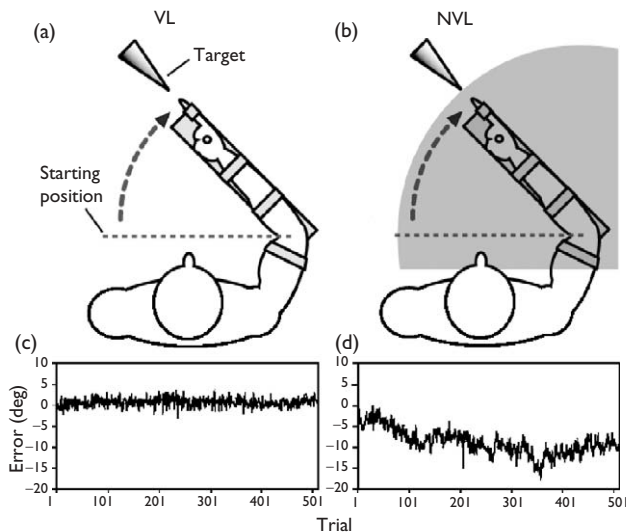


Fig. 1. Experimental apparatus for the VL (visible limb; **a**) and the NVL (non-visible limb; **b**) conditions. The gray-colored field in (**b**) is the invisible field for subjects created by a board. Example error sequences for the VL (**c**) and NVL (**d**) conditions from one subject.

Task and experimental procedure: Subjects performed discrete visual-target directed movements. In response to a beep, the subjects extended their right elbow from the starting position to point to the tip of the target cone with their index fingertip (movement amplitude 45° ; Fig. 1a). After a short pause the subjects returned their forearm to the starting position and waited for the next beep. While performing the task, the subjects constantly gazed on the tip of the target cone. The subjects were instructed to perform smooth and accurate movements at a comfortable speed. This movement was repeated for 522 trials (inter-trial interval 2.5 s) for each of the following two conditions. In the visible limb (VL) condition (Fig. 1a), the subjects could compare their fingertip location with the external target location directly on the visual coordinate frame. On the other hand, in the non-visible limb (NVL) condition (Fig. 1b), a board was placed so that subjects could see only the target and not their controlling upper limb. The subjects therefore depended on kinesthesia to match their fingertip location to the visually presented target location. The mechanical manipulandum stopper was set so that subjects could return their forearm to the starting position without using vision. Trials in these two conditions were performed in separate sessions, and subjects were allowed to take a 20 min rest between sessions. The order of the two conditions was counterbalanced across subjects. Prior to the above experimental sets, there was a practice set (128 trials) for each condition.

Basic kinematic features of movements performed in our experiment were as below. The peak velocity across subjects was 150.20 ± 19.92 and $108.04 \pm 19.82^\circ/\text{s}$ for the VL and NVL condition respectively. The movement time (movement onset threshold = $5^\circ/\text{s}$) across subjects was 730.79 ± 106.01 and 723.97 ± 87.88 ms for the VL and NVL condition respectively.

Data analysis: The movement endpoint was calculated as the first velocity zero-cross position after the peak velocity. For the following analysis, we used the movement-endpoint error of the last 512 trials in each condition. The constant

(systematic) error was calculated as the mean value of errors for each sequence: positive values indicate a movement overshooting of the target, while negative values indicate undershooting. The variable error was calculated as the s.d. of errors for each sequence. After removing the mean and normalizing by the s.d. for the individual sequences, we analyzed the error series using two methods of scaling analysis: power spectral analysis and detrended fluctuation analysis (DFA).

Power spectral analysis: Power spectral analysis is the major scaling analysis method. For a sequence with fractal time correlation, its power spectrum $S(f)$ has a power law form: $S(f) \sim 1/f^\beta$, where f is frequency. The spectral exponent β represents the degree of time correlation for the sequence [7,9]. For a sequence with no time correlation, i.e., white noise, $\beta = 0$. If $\beta > 0$, the series is considered to have fractal correlation. $\beta = 2$ indicates brown noise, the accumulation of white noise. In the case of $\beta = 1$, the sequence is $1/f$ noise, which is an intermediate state between random white noise and highly structured brown noise.

We computed β as the slope ($-\beta$) of the power spectrum in a double logarithmic scale for the frequencies between $10^{-2.51}$ and 10^{-1} Hz, corresponding to window sizes between 4 and 128.

DFA: DFA [7,10] is a modification of classical random walk analyses and has important advantages over other scaling analyses: it is relatively unaffected by any nonstationarities because it subtracts (detrends) a locally best-fit line before it performs the fluctuation analysis. For a time series with fractal correlation, the fluctuation function $F(n)$ has a power-law form: $F(n) \sim n^\alpha$, where n is window size. The DFA exponent α is determined by computing the slope of the regression line relating $\log F(n)$ to $\log n$. In the case of $\alpha = 0.5$, the sequence is white noise. If $\alpha > 0.5$, the series is considered to have time correlation. $\alpha = 1.5$ indicates brown noise. In the case of $\alpha = 1$, the sequence is $1/f$ noise.

In the procedure in which the integrated time series was divided into time windows of size n , we set a 50% overlap between windows. We performed the DFA for window size ranges between 4 and 128.

The use of both spectral and random walk analyses is necessary not only to reveal the true nature of a given process, but also to avoid the false conclusion of scaling behavior resulting from possible artifacts or wrong measurements [11].

Surrogate data test: To test the statistical significance for the time correlation, i.e. $\beta > 0.5$ and $\alpha > 0.5$, we applied the method of surrogate data [12]. For each error series, 20 surrogate data sets were generated by randomly shuffling the temporal order of the original data set. Hence, the surrogate data set, like white noise, lost time correlation. The mean and s.d. of each scaling exponent were calculated for the shuffled surrogate data sets. Then the number of s.d. between the original scaling exponent and the mean scaling exponent of 20 surrogate data (σ) was computed. If $\sigma > 3$, the sequence was considered to have significant time correlation ($p < 0.05$).

RESULTS

The constant error across subjects was $0.74 \pm 0.58^\circ$ and $-9.83 \pm 3.93^\circ$ for the VL and NVL condition respectively.

The difference between them was significant ($p < 0.001$, paired t -test). Similarly, the variable error across subjects for the NVL condition ($3.34 \pm 0.81^\circ$) was larger than that for the VL condition ($1.04 \pm 0.17^\circ$; $p < 0.001$). The substantial constant undershooting observed in our experiments was approximately in accordance with the observation of Soechting and Flanders [1].

The notable property in this study is the sequential profile for error. The error sequence for the VL condition showed a stationary pattern around error=0 (Fig. 1c), while the sequence for the NVL condition exhibited a characteristic undulating pattern (Fig. 1d). To summarize the results of power spectral analyses, Fig. 2 shows the averaged log-log power spectra of the error sequences. For the VL condition, the spectrum exhibited a relatively flat pattern (Fig. 2a); a steeper negative slope was observed in the spectrum for the NVL condition (Fig. 2b). The upper part of Table 1 shows that the β value across subjects was 1.05 ± 0.17 for the NVL condition, which was larger than 0.16 ± 0.29 for the VL condition ($p < 0.001$, Mann-Whitney test), indicating that the error sequence for the NVL condition has a stronger time correlation than that for the VL condition.

Figure 3 shows the averaged detrended fluctuation functions $F(n)$ in a log-log scale. The slope of the averaged $F(s)$ was steeper for the NVL condition (Fig. 3a) than for the VL condition (Fig. 3b). The bottom part of Table 1 shows that the α value across subjects was 1.02 ± 0.12 for the NVL condition, which was larger than 0.68 ± 0.09 for the VL condition ($p < 0.001$). Similar results were, therefore, observed commonly in both scaling exponents.

Table 2 shows the results of the surrogate data tests. For the VL condition, the σ for β across subjects was 0.92 ± 2.17 . For the α , the σ across subjects was 3.19 ± 1.78 , and $\sigma > 3$ occurred only in three of eight subjects. Thus, in the VL condition, the correlation for the error series could not clearly be distinguished from that for white noise. On the other hand, for the NVL condition, the σ across subjects was 5.83 ± 1.34 for β and was 9.85 ± 2.39 for α , much greater than 3. That is, the error series for the NVL condition is considered to have a significant fractal time correlation.

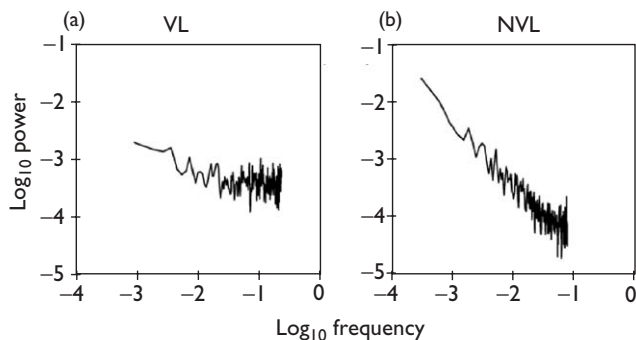


Fig. 2. Averaged power spectra across subjects for the error sequences for the VL (a) and NVL (b) conditions in a log-log scale.

Table 1. Across-subject values for the spectral exponent β and the DFA exponent α for the VL and NVL conditions.

	VL	NVL
β	0.16 ± 0.29	1.05 ± 0.17
α	0.68 ± 0.09	1.02 ± 0.12

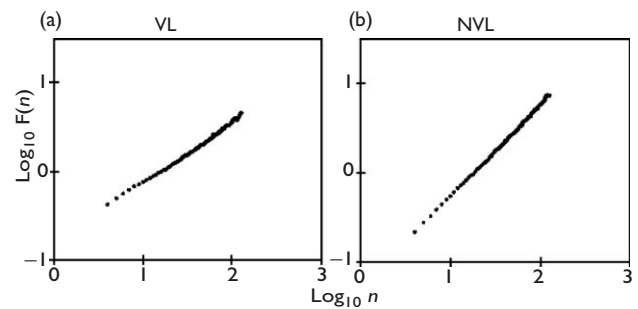


Fig. 3. Averaged detrended fluctuations across subjects for the error sequences for the VL (a) and NVL (b) conditions in a log-log scale.

Table 2. Results of the surrogate data test: across-subject values of the σ s for β and α . The fraction within the parentheses shows the ratio of the subjects whose σ values were statistically significant (i.e., $\sigma > 3$) in each across-subject value of σ .

	VL	NVL
σ for β	0.92 ± 2.17 (1/8)	5.83 ± 1.34 (7/8)
σ for α	3.19 ± 1.78 (3/8)	9.85 ± 2.39 (8/8)

DISCUSSION

The errors in sensory-target directed movements without moving-limb vision have been used to elucidate the properties of human sensorimotor transformation [1–4]. In this study, we investigated the error sequences for visual-target directed movements using scaling analyses. For the VL condition, the error sequence could not be distinguished from uncorrelated white noise, but in the NVL condition the error sequence had strong fractal time correlation (spectral exponent $\beta \approx 1$, DFA exponent $\alpha \approx 1$). This result indicates that the variation in human visuomotor transformation is considered to be $1/f$ -type fluctuation. Although, at this stage, it is not clear what mechanisms cause the $1/f$ -type correlation in human visuomotor transformation dynamics, this phenomenon provides a significant index for future studies of human visuomotor transformation or integration, especially for mathematical-modeling and system-identification studies.

For the last decade, the fractal correlation has been demonstrated in the variation sequence in some types of human motor behavior [5–9]. In mathematical modeling for walking [7] and rhythm tapping [8,9], the existence and degree of the fractal correlation in the output sequence of the invented model have been the critical guideposts for their validity. The mathematical modeling approach is also an important branch in the investigation of human spatial sensorimotor transformation and integration [13,14]. In this field, the test for the existence and degree of fractal correlation in model simulation ought to be a significant indicator for verifying the existing model and evolving the new one. This test can at the same time lead to the elucidation of the etiology of the fractal correlation in human sensorimotor systems.

A number of mechanisms have been proposed to explain the occurrence of $1/f^\beta$ -type fluctuations, in some of which, a central theme of these models is the presence of multiple interacting components acting on different time scales [9]. In line with this concept, the fractal behavior such as $1/f^\beta$ -type fluctuations arises not from a single component but from the

interaction of multiple components acting on different time scales. The multiple-component concept has also arisen in progress of the internal-model hypothesis for human goal-directed movement control [15]. It may be that each of the theoretical multiple internal models would have a different time-scale property than the others, and the interactions of them would be the origin of $1/f$ -type fluctuation in human visuomotor transformation.

The human visuomotor system has frequently been investigated using various types of experimental manipulation for the relation between visual inputs and motor outputs [16,17], in which a single-step type of change was conventionally used. However, the changes arising in our daily environment ought to be noise-like random variations. Based on this conviction, Sheidt *et al.* [18] used a random-variation (white-noise) type of viscous-field perturbation to the upper limb. Subsequently, assuming the change occurring in sensory-motor mapping was attributable to an accumulation of random variations, Baddeley *et al.* [19] used a random-walk (brown-noise) type of visuomotor perturbation for system identification. However, as observed in the present study, the variation occurring in the non-calibrated visuomotor mapping could be categorized neither as white noise nor brown noise but as a statistically intermediate state between them, namely $1/f$ noise. In order to identify the human visuomotor system using the most real type of variable perturbation, one must adopt the $1/f$ -type fluctuation to the perturbation.

The utilization of the $1/f$ -type fluctuation for visuomotor perturbations cannot be merely the highly rigid imitation of the variations in the real human visuomotor system because the addition of the $1/f$ -type fluctuation to certain neuronal systems generates different effects on the system responses from those of the white- and brown-type of variations and, furthermore, the $1/f$ -type fluctuation can be an optimal state to sensitize the neuronal signal responses. It is known that stochastic noise can assist neuronal systems in the detection of weak signals [20]. A numerical simulation study using the FitzHugh–Nagumo model showed that the patterns of signal input-output coherence as a function of added-noise intensity were different among the added-noise types, white, brown, and $1/f$, and that the noise intensity needed to maximize the coherence was smallest when the $1/f$ -type noise was added [21]. A similar phenomenon was observed in rat sensory neurons [22]. In humans, the addition of $1/f$ -noise more effectively sensitized baroreflex centers than that of white noise [23]. It is also possible that, on the human visuomotor system, the $1/f$ -type perturbation makes different effects than the white- and brown-noise types of perturbations. The application of the $1/f$ -type fluctuation as a visuomotor perturbation has the possibility of providing novel and more essential information for the identification of the human visuomotor system.

CONCLUSION

Using power spectral analysis and DFA, we investigated the trial-by-trial sequential property of the error in limb movements toward visual target. When subjects could see their controlling limb, the error sequence exhibited a weak correlation which could not be distinguished from a random sequence, i.e., white noise. On the other hand, when the

subject's limb was invisible, the error sequence had a strong fractal time correlation (spectral exponent $\beta \approx 1$, DFA exponent $\alpha \approx 1$). This result indicates that the variation in human visuomotor transformation is considered to be $1/f$ -type fluctuation. This finding provides a significant index for studies of human visuomotor control, especially for mathematical modeling and system identification studies.

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