Residual Movement Analysis and Human Motor Control

Ing-Shiou Hwang, Ph.D., P.T.
Department of Physical Therapy
National Cheng Kung University
Tainan, Taiwan
人體電生理實驗室—2000年成立

### 人體電生理訊號量測

- 多頻道肌電圖 (Electromyography, EMG)
- 神經傳導速度 (Nerve conduction velocity, NCV)
- 神經反射 (H reflex, Cutaneumuscular reflex, etc.)
- 肌音圖 (Machanomyogram, MMG)
- 腦電圖 (Electroencephalogram, EEG)
- 心電圖 (Electrocardiogram, ECG)
- 震顫訊號 (Laser, accelerometer)
- 皮電阻抗訊號
- 眼球運動軌跡
Background for Residual Movement Analysis

Mathematics
- Digital Filtering
- Gaussian Decomposition
- Empirical Mode Decomposition (EMD)
- Multi-scale Entropy

Physics
- Position, Velocity, Force

Physiology
- Muscle, Nerve, Eye, Brain
Outlines

I. Preview of Residual Movements
   - Movement prototype, submovement, motor noises

II. Discrete and Continuous Submovements
   - Examples of arm-reaching and rhythmic contracting
   - Mathematical approaches
     - Feature extraction - Gaussian Decomposition, EMD, Digital filtering
     - Feature analysis - Kurtosis, Skewness, Multi-scale complexity

III. Experiment Data and Implication
   - Motor learning, motor performance
1. Preview --
I. Preview

WRITE (with dominant hand only) "TODAY IS A NICE DAY IN BALTIMORE," SIGN YOUR NAME AND WRITE THE DATE JULY 4, 1776.

day is a nice day in Baltimore
July 4, 1776
A voluntary motor act is composed of:

1) **Movement prototype** (原型運動)

2) **Submovement** (子運動)
   - Sinusoidal movement, circular movement, and point-reaching are frequently investigated
   - Intermittent error detection and correction process
   - Discrete block of single-peaked, bell-shaped speed profile
   - Smooth acceleration and deceleration for error correction.
   - Modifiable to sensory feedback (vision, proprioception etc) or feed-forward process

3) **Motor noise** (運動雑訊)
II. Submovement – sinusoidal tracking

Fig. 2. Typical responses during sinusoidal tracking at 3 frequencies. The target sinusoids are not shown. Monkey position records are on the left with corresponding velocity records on the right. A: 0.15 Hz; B: 0.3 Hz; C: 0.71 Hz; ordinates in cm (left) or cm/s (right); 1 cm is ca. 2°.
II. Submovement – sinusoidal tracking

Because we were interested in the movement in the target area independent of the movement of the target area itself, the motion of the target was subtracted

\[ \varphi_{\text{rel}}(t) = \varphi(t) - A \sin(2\pi t/\Gamma) \]
Impedance Modulation and Feedback Corrections in Tracking Targets of Variable Size and Frequency

Luc P. J. Selen, Jaap H. van Dieën, and Peter J. Beek

Institute for Fundamental and Clinical Human Movement Sciences, Faculty of Human Movement Sciences, Vrije Universiteit, Amsterdam, The Netherlands

Fig. 3. Tracking variability. A: section of an experimental time series of elbow angle (black line) and target area (gray area). Vertical lines, boundaries of cycles. B: superposition of cycles (black lines) and target area (gray area). C: mean angle (black line) and 95% CI (gray area) over cycles. D: positional SD over movement cycles. Motor output variability was expressed as Ave-PosSD and calculated by taking the mean of the time series in D.

Fig. 1. Experimental set-up of target tracking experiment. Top: front-side view of a subject with the subject’s forearm cast onto a lightweight bar attached to the motor. Bottom: LED array with target to be tracked and laser projection.
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FIG. 7. SP gain for a single subject for 3 movement frequencies (columns) and 3 target sizes (rows). SP gain is the regression slope of SP duration vs. SP amplitude.
II. Submovement – circular tracking

S. Pasalar · A. V. Roitman · T. J. Ebner

Effects of speeds and force fields on submovements during circular manual tracking in humans
Fig. 2 Plot of the speed profile from a single trial in relation to the Hold, Cue, Intercept, and Track periods (task timeline shown above the graph). *Inset* is a speed pulse extracted from the speed profile. The various measures used to define a speed pulse are shown including start speed ($S_{start}$), end speed ($S_{end}$), amplitude ($\Delta S$), and duration ($\Delta T$).

- 調節子活動振幅波寬的組合是不同速度動作的控制基礎
Deciding when and how to correct a movement: discrete submovements as a decision making process

Alon Fishbach · Stephane A. Roy · Christina Bastianen · Lee E. Miller · James C. Houk

Fig. 1. Schematic representation of the experimental setup. Subjects moved the fingertip to one of the four targets on the horizontal table. The arm was positioned horizontally above the table. Movements were performed via the shoulder and elbow rotations with the immobilized trunk and wrist. Although the targets are shown in the plane of motion, they were presented on the computer screen and not on the table. In addition to the targets, the computer screen showed a cursor that represented motion of the fingertip.

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II. Submovement – motor noise
II. Submovement – motor noise
II. Submovement – signal processing

Signal Conditioning

Positional Trace
- Low Pass Filtering (6Hz)
- Differentiation

Velocity Trace

Feature Extraction
- Gaussian Decomposition
- Notch Filtering
- Empirical Mode Decomposition

Feature Analysis
- Multi-scale Entropy
- Component Statistics
II. Submovement – signal processing

Signal Conditioning

- Positional Trace
  - Low Pass Filtering (6Hz)
  - Differentiation
- Velocity Trace

Feature Extraction

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- Notch Filtering
- Empirical Mode Decomposition

Feature Analysis

- Multi-scale Entropy
- Component Statistics
Submovement functions as support-bounded lognormal (LGNB) curves

$$B(t) = \frac{D(T_1 - T_0)}{\sigma \sqrt{2\pi}(t - T_0)(T_1 - t)} \exp\left\{ \left( \frac{-1}{2\sigma^2} \right) \left[ \ln\left( \frac{t - T_0}{T_1 - t} \right) - \mu \right]^2 \right\}$$ (1)

for $T_0 \leq t \leq T_1$ where $D$ is the displacement resulting from the movement, $T_0$ is the movement start time, $T_1$ is the end time, $\mu$ controls the skewness (asymmetry), and $\sigma$ determines the kurtosis (“fatness”) of the curve. The five independent

**Rohrer et al. (2004).**

\[
\epsilon = \frac{\int |F(t) - G(t)|dt}{\int |G(t)|dt}
\] (2)

with $G(t)$ the movement speed profile and $F(t)$ the extracted speed profile. In this study $\epsilon$ was set to 2%.
Special issue: Research report

Submovement changes characterize generalization of motor recovery after stroke

Laura Dipietro\textsuperscript{a,},\textsuperscript{,*} Hermano I. Krebs\textsuperscript{a,\textsuperscript{b,\textsuperscript{c}},} Susan E. Fasoli\textsuperscript{d}, Bruce T. Volpe\textsuperscript{b} and Neville Hogan\textsuperscript{a,\textsuperscript{e}}

*Cortex 45 (2009) 318-324

Fig. 3 – Top figure: submovement decomposition of the speed profile of the shapes shown in Fig. 1, top. Bottom figure: submovement decomposition of the speed profile of the shape shown in Fig. 1, bottom.
II. Submovement – Gaussian decomposition

Avoiding spurious submovement decompositions: a globally optimal algorithm

Brandon Rohrer¹, Neville Hogan²

¹ Intelligent Systems and Robotics Center, Sandia National Laboratories, PO Box 5800, Albuquerque, NM 87185, USA
² Department of Mechanical Engineering and Department of Brain and Cognitive Science, Massachusetts Institute of Technology, 77 Massachusetts Ave., Cambridge, MA 02139, USA

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II. Submovement – signal processing

Signal Conditioning

- Positional Trace
  - Low Pass Filtering (6Hz)
  - Differentiation
- Velocity Trace

Feature Extraction

- Gaussian Decomposition
- Notch Filtering
- Empirical Mode Decomposition

Feature Analysis

- Multi-scale Entropy
- Component Statistics
II. Submovement – signal processing

Velocity Trace

\[ V(t) = P_n(t) \times G + S_n(t) + e(t) \]

High-Q Notch anti-phasing filter (fT)

Velocity Trace without fT

Velocity Trace with fT

\[ \text{Min } e(t) \]

X Gain (0.9-1.1)

Submovement + Noise

Movement prototype

[Diagram showing velocity traces and filter characteristics]
II. Submovement – signal processing

- Notch filter could in theory be realised with two zeros placed at $\pm j\omega_0$. However, such a filter would not have unity gain at zero frequency, and the notch will not be sharp.
- To obtain a good notch filter, put two poles close the two zeros on the semicircle as shown. Since the both pole/zero pair are equal-distance to the origin, the gain at zero frequency is exactly one. Same for $\omega=\pm\infty$.

- Design a second-order notch filter to suppress 60 Hz hum in a radio receiver.
- Make $\omega_0=120\pi$. Place zeros are at $s = \pm j\omega_0$, and poles at $-\omega_0 \cos \theta \pm j\omega_0 \sin \theta$.
- We get:

$$H(s) = \frac{(s - j\omega_0)(s + j\omega_0)}{(s + \omega_0 \cos \theta + j\omega_0 \sin \theta)(s + \omega_0 \cos \theta - j\omega_0 \sin \theta)}$$

$$= \frac{s^2 + \omega_0^2}{s^2 + (2\omega_0 \cos \theta)s + \omega_0^2} = \frac{s^2 + 142122.3}{s^2 + (753.98 \cos \theta)s + 142122.3}$$
III. Experiment Data - Learning

- Force Trace
- Sinusoidal primary movement
- Submovement

- Speed pulse trace

- Submovement

- Speed Pulse

- Amplitude

- Duration

- Time (Second)
  12 13 14 15 16

- Force Pulse

- 2 Kg
II. Submovement – signal processing

Signal Conditioning

Positional Trace

- Low Pass Filtering (6Hz)
- Differentiation

Velocity Trace

Feature Extraction

- Gaussian Decomposition
- Notch Filtering
- Empirical Mode Decomposition

Feature Analysis

- Multi-scale Entropy
- Component Statistics
Empirical Mode Decomposition (EMD)

II. Submovement - EMD

Empirical Mode Decomposition (EMD)

Purpose

- Decompose non-stationary and non-linear signal into intrinsic mode functions (IMF) (Norden E. Huang, 黃鍔)

**IMF:**

a) The number of extrema and the number of zero-crossing must either equal or differ at most by one

b) At any point, the mean value of the envelope defined by the local maxima and the envelope defined by the local minima is zero. (ex. sine wave)

![Image of wind speed graph](image-url)

*Figure 2. A typical intrinsic mode function with the same numbers of zero crossings and extrema, and symmetry of the upper and lower envelopes with respect to zero.*
Empirical Mode Decomposition (EMD)

Assumption

1. the signal has at least two extrema: one maximum and one minimum
2. the characteristic time scale is determined by the time lapse between the extrema.
3. if the data were totally devoid of extrema but contained only inflection points, then it can be differentiated once or more times to reveal the extrema.

The empirical mode decomposition method:

The sifting process
步驟 1: 找出 $s(t)$ 中的所有局部極大值以及局部極小值，接著利用三次樣條 (cubic spline)，分別將局部極大值串連成上包絡線與局部極小值串連成下包絡線。

步驟 2: 求出上下包絡線之平均，得到均值包絡線 $m_1(t)$。

步驟 3: 原始信號與均值包絡線相減，得到第一個分量。$h_1(t) = s(t) - m_1(t)$。

步驟 4: 檢查是否符合 IMF 的條件。如果不符合，則回到步驟 1 並且將當作原始訊號，進行第二次的篩選。亦即 $h_2(t) = h_1(t) - m_2(t)$。

重複篩選 $k$ 次，直到符合 IMF 的條件，即得到第一個 IMF 分量，亦即 $h_k(t) = h_{k-1}(t) - m_k(t)$，$c_1(t) = h_k(t)$。

步驟 5: 原始信號 $s(t)$ 減去 $c_1(t)$ 可得到剩餘量 $r_1(t)$，表示如下式 $r_1(t) = s(t) - c_1(t)$。

步驟 6: 將當作新的資料，重新執行步驟 1 至步驟 5，得到新的剩餘量。如此重複次 $r_2(t) = r_1(t) - c_2(t)$，$r_3(t) = r_2(t) - c_3(t)$，

\[ \ldots r_n(t) = r_{n-1}(t) - c_n(t) \]

當第個剩餘量已成為單調函數 (monotonic function)，將無法再分解 IMF 時，整個 EMD 的分解過程完成。原始訊號 $s(t)$ 可以表示成個 IMF 分量 $r_n(t)$ 與一個平均趨勢 (mean trend) 分量的組合，亦即

$$ s(t) = \sum_{k=1}^{n} c_k(t) + r_n(t) $$

原始資料便分解成 n 個 IMF 和一個趨勢函數。
Let $x(t)$ be a velocity signal to be composed.
II. Submovement – EMD  The Sifting Process

Empirical Mode Decomposition (EMD)

Identify all local maxima of \( x(t) \):
Identify all local minima of $x(t)$:
II. Submovement – **EMD**  *The Sifting Process*

**Empirical Mode Decomposition (EMD)**

Interpolate between maxima ending up with some envelope $max(t)$
II. Submovement – EMD

The Sifting Process

\[ e_{\min(t)} : \]

Empirical Mode Decomposition (EMD)

Likewise for the minimal envelope \( min(t) \)
Empirical Mode Decomposition (EMD)

Compute \( m_1(t) = 0.5 \times [\text{max}(t) + \text{min}(t)] \)
II. Submovement – EMD

The Sifting Process

4. Extract the detail $d(t) = x(t) - m(t)$

Empirical Mode Decomposition (EMD)

Extract $IMF_1(t) = x(t) - m_1(t)$

Iteration like $x(t)$
Empirical Mode Decomposition (EMD)

II. Submovement – EMD

The Sifting Process

Iterate on the residual $m(t)$ until the number of extrema in the signal is less than 2.

Extract $IMF_2(t) = m_1(t) - m_2(t)$  $\rightarrow$ Iteration like $x(t)$
We finally obtain the decomposition of the signal:

\[ x(t) = \sum_{k} \phi_k(t) + r(t) \]

Empirical Mode Decomposition (EMD)

**II. Submovement – EMD**

*The Sifting Process*

**Empirical Mode Decomposition**

- IMF_1(t)
- IMF_2(t)
- IMF_3(t)
- IMF_4(t)
- e(t)

\[ x(t) = \sum_{k} IMF_k(t) + e(t) \]
II. Submovement — EMD

The empirical mode decomposition and the Hilbert spectrum for nonlinear and non-stationary time series analysis

By Norden E. Huang¹, Zheng Shen², Steven R. Long³, Manli C. Wu³, Hsing H. Shih⁴, Quan-an Zheng⁵, Nai-Chyuan Yen⁶, Chi-Chao Tung⁷ and Henry H. Liu⁸

II. Submovement – signal processing

Signal Conditioning

Positional Trace
Low Pass Filtering (6Hz)
Differentiation
Velocity Trace

Feature Extraction
Gaussian Decomposition
Notch Filtering
Empirical Mode Decomposition

Feature Analysis
Multi-scale Entropy
Component Statistics
Figure 2: A simulated time series $u[1], \ldots, u[n]$ is shown to illustrate the procedure for calculating sample entropy (SampEn) for the case in which the pattern length, $m$, is 2, and the similarity criterion, $r$, is 20. ($r$ is a given positive real value that is typically chosen to be between 10% and 20% of the sample deviation of the time series.) Dotted horizontal lines around data points $u[1]$, $u[2]$ and $u[3]$ represent $u[1] \pm r$, $u[2] \pm r$, and $u[3] \pm r$, respectively. Two data values match each other, that is, they are indistinguishable, if the absolute difference between them is $\leq r$. All green points represent data points that match the data point $u[1]$. Similarly, all red and blue points match the data points $u[2]$ and $u[3]$, respectively. Consider the 2-component green-red template sequence ($u[1], u[2]$) and the 3-component green-red-blue ($u[1], u[2], u[3]$) template sequence. For the segment shown, there are two green-red sequences, ($u[13], u[14]$) and ($u[43], u[44]$), that match the template sequence ($u[1], u[2]$) but only one green-red-blue sequence that matches the template sequence ($u[1], u[2], u[3]$). Therefore, in this case, the number of sequences matching the 2-component template sequences is two and the number of sequences matching the 3-component template sequence is 1. These calculations are repeated for the next 2-component and 3-component template sequence, which are, ($u[2], u[3]$) and ($u[2], u[3], u[4]$), respectively. The numbers of sequences that match each of the 2- and 3-component template sequences are again counted and added to the previous values. This procedure is then repeated for all other possible template sequences, ($u[3], u[4], u[5]$), ..., ($u[N-2], u[N-1], u[N]$), to determine the ratio between the total number of 2-component template matches and the total number of 3-component template matches. SampEn is the natural logarithm of this ratio and reflects the probability that sequences that match each other for the first two data points will also match for the next point.
Sample Entropy is the negative natural logarithm of an estimate of the conditional probability that subseries (epochs) of length m that match pointwise within a tolerance r also match at the next point.
Fig. 1: Schematic illustration of the coarse-graining procedure for scale 2 and 3. Adapted from reference [8].

The element of the coarse-grained time series, $y_j^{(\tau)}$, is calculated according to the equation:

$$y_j^{(\tau)} = \frac{1}{\tau} \sum_{i=(j-1)\tau+1}^{j\tau} x_i$$  \hspace{2cm} (1)

where $\tau$ represents the scale factor and $1 \leq j \leq N/\tau$. The length of each coarse-grained time series is $N/\tau$. For scale 1, the coarse-grained time series is simply the original time series.
Figure 3: MSE analysis of simulated white and 1/f noise time series. Symbols represent mean values over 30 time series. Parameters to calculate sample entropy are: $m = 2$, $r = 0.15$, and $N = 30,000$. Adapted from reference [2].
III. Experiment Data

Topics

1. Practice-related changes in submovement under different target conditions.
2. Fatigue and submovement
III. Experiment Data - Learning

Experiment Procedure

Thirty-six subjects

- Simple: n=12
- Complex: n=12
- Random: n=12

Pre-test session
  Test Trial*3
  20 minutes

Practice session
  Practice Block (#1~#15)
  Inter-block Period: 30 seconds
  1 hour

Post-test session
  Test Trial*3

Data Collection

- Laser
- Laser spot
- Target Position
- Tracking Position
- ED EMG
- FDS EMG

Data Processing

- A/D card
- Computer

Graphs showing EMG waveforms for different conditions:
- Simple
- Complex
- Random
III. Experiment Data - Learning

III.  Experiment Data - Learning
III. Experiment Data - Learning

- 動作耦合程度隨有效學習而增加
- 子活動功率隨有效學習而降低
III. Experiment Data - Learning

- Activity complexity increases with effective learning.

![Graphs showing SampEn and MSE area for Simple, Complex, and Random conditions across different scale factors and block numbers.](image-url)
III. Experiment Data - Fatigue

Pre-Fatigue

Post-Fatigue

Force (Newton)

Time (Second)

Dynamometer

Gripping Hand

EMG

Pre-fatigue Trial → Fatiguing Ex → Post-fatigue Trial

0.5 Hz Sinusoidal tracking 50-100% MVC
III. Experiment Data - Fatigue

- Power Ratio of Prototype Movement to Residual movement

- 疲勞發生贅餘活動相對於原型活動的比率增高
### III. Experiment Data - Fatigue

**Speed Pulse Gain**

- **Pre-fatigue**
  - **Duration (Sec):** 0.0, 0.2, 0.4, 0.6, 0.8
  - **Amplitude (Nt):** 0, 2, 4, 6, 8, 10, 12, 14, 16, 18
  - Equation: $y = 15.95x + 3.67$
  - Correlation: $r = 0.763$

- **Post-fatigue**
  - **Duration (Sec):** 0.0, 0.2, 0.4, 0.6, 0.8, 1.0
  - **Amplitude (Nt):** 0, 2, 4, 6, 8, 10, 12, 14, 16, 18
  - Equation: $y = 8.93x + 1.47$
  - Correlation: $r = 0.620$

- **Pulse Amplitude (Nt)**
  - **Pre:** 9.49 (0.56)
  - **Post:** 4.60 (0.45)

- **Pulse Duration (Sec)**
  - **Pre:** 0.414 (0.006)
  - **Post:** 0.362 (0.008)

- **Remarks:** 疲勞使speed pulse產生模式發生改變
III. Experiment Data - Fatigue

Post = Pre + 1/f noise * 1/6

Fatigue Index?

Prototype

Fractalized?

Submit

Noise

Karhunen-Loève transform?
Discrete cosine transform?
Other??

Fatigue

n=16

1/f noise

MSE

Post-fatigue

Pre-fatigue

• 疲勞發生贅餘活動複雜度發生改變~

Discrete cosine transform?
Thank you!

Aal Izz Well!