Characterizing Force Variability in Human Grasping during Dynamic Force Speed vs. Accuracy Trade-off (DSAT) task

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I. Abstract : Grasping an object with properly controlled force is one of the omnipresent and fundamental tasks in human motor behaviour, yet its control by the nervous system is poorly understood. This study analyses dynamic motions during targeted grasping task to better understand human motor control system. Five healty subjects performed dual target task with various force amplitudes while cued by a visual feedback from a computer display. Non-linear, semi-isometric gripper was developed consisting of a cylinder with an array of force sensing resistors[1] (FSR) on the surface to detect global force output of the hand. Tasks were performed wherein the user was required to match his grip force to two given targets in turn as many as possible in a given time period, with the distance between targets increasing into 5 steps in a timed manner. The result was analyzed in terms of force accuracy and stability by hit score, force variability and approximate entropy (ApEn). The result showed a proportional relationship between force variability and the force magnitude which agrees well with other literatures[5,7]. It also showed a similar logarithmic relationship between index of difficulty and measurement time which also agrees well with the well-known kinematic speed and accuracy test (KSAT) described by Fitts' law[2].

II. Introduction : Our previous work has provided hemiplegic users with realistic and challenging environments in which to learn manipulation skills[3,4]. Recently we developed a Grasp Reinforcement Interface Program (GRIP) for analyzing grasp control. The system displays muscular activity of the forearm during grasping motions using the gripper, a myokinetic interface (MKI) device, and requires the user to match muscular output at requested levels from very low to his maximum. Logarithmic relations were found from DSAT along with force variability characteristics and ApEn. Result agrees well with previous literatures in human motor control theories [5].

Previous kinesiology theory describes a plateau of maximal motor accuracy over time regardless the effects of task-specific adaptation or learning[2]. There also exists a kinematic speed vs. accuracy trade-off trend, another intrinsic human motor behavior[1]. Traditional motor analysis views these limits as an intrinsic systematic noise or variability in terms of information theory[6], where our body functions as a neuromotor channel through which a motor signal from the brain conducts down to motor end effectors to achieve certain tasks[2,5].

This research also applies other matrices to describe force characteristics to understand human motor behaviour, such as force variability[5] and ApEn[6].

: Logarithmic Relationship in KSAT (Fitts' Law).

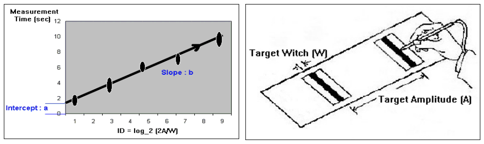

Fig.1 Examplary Plot of Logarithmic Relationship in Fitts' Law (left) and KSAT test (right).

$$MT = a + b \cdot log_2(2A/W)$$

where, A = distal amplitude between targets
W = width of the target
a = intercept on ordinate
b = slope
$log_2(2A/W)$ = the index of difficulty (ID)

–Conventional (spatial, kinematic) Fitt's Law.
–The faster we move, the less accurate we become,
– Haste makes waste.

IV. Results

: Logarithmic Relationship in DSAT.

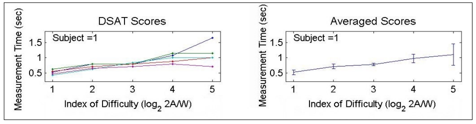

Fig.4 Score Plot of DSAT test from subject 1, showing similar logarithmic relations to KSAT.

Result showed a very good linear regression fit of higher than 0.99.

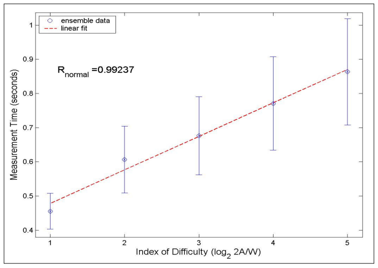

Fig.5 Linear fit of all subjects' averaged score.

: Approximate Entropy (ApEn)

Non-linear dynamic system's predictability over time can be described by ApEn[6] in a single scalar value. ApEn is a new statistical analysis which provides an index of the system noisiness (high ApEn) or predictability (low Apen) toward future events in a time series, based on previous time-series data. (Ex : $ApEn_{White\ noise} > 1$, $ApEn_{HR} \cong 0$).

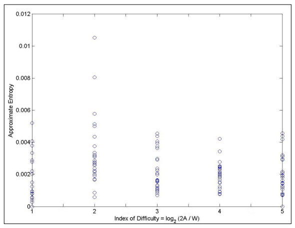

Fig.6 ApEn plot. Max noisiness scatter at ID 2 (= 50 %MVC).
(Note: ID 1~5 represents 30, 50, 67, 80 and 90 %MVC respectively.)

IV Results (Cont.) : Force-time Profile and Force Variability. Accumulative graphs for overall force-time profile show an overall trend of subject's force output with common overshoots. Relatively more overshoots (hairline trails outside overall volume) seen in decreasing force production (descending vectors) than in ascending vectors (Fig.7). Similar trend can be noticed on force variabilities (Fig.8), indicating higher volumatric trails during decreasing force production.

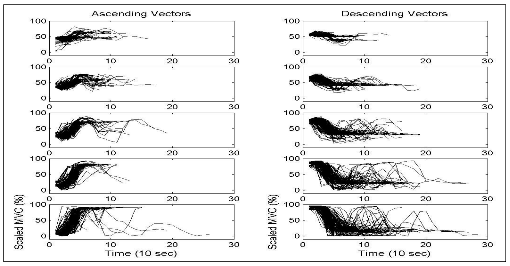

Fig.7 Force-time profile, all subjects.

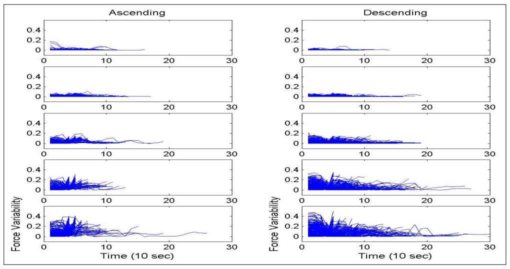

Fig.8 Force variability, all subjects.

V. Conclusion : DSAT test using GRIP system showed a very high linear regression fit coefficient (R=0.99237), with a similar logarithmic trend to KSAT test. Approximate entropy (ApEn) showed a mid-level maximal force structure noisiness at 50 %MVC. Force variability showed a proportional relations between the force magnitude and force variability.

All results agreed well with previous literatures, which suffices us to say that the GRIP system is a reliable force monitoring system for dynamic motor control analysis.

III. Methods : Subjects were asked to hit (match) the target as many as possible in a given time period (30 sec) per each target gaps. The tank's 0 to 1 scale is mapped non-linearly to represents subject's %MVC (Maximal Voluntary Contraction) levels, for 5 target gap per from ID 1 to 5 (= 30, 50, 67, 80, 90 %MVC). Each gaps are centered at 0.5 on the tank's scale (67% MVC).

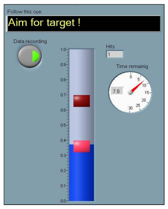
Follow this cue.
Aim for target !
Data recording
Hits 1
Time remainig 7.6

Fig.2 LabVIEW GRIP interface for DSAT.

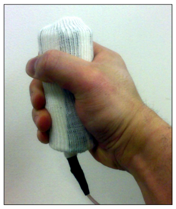

Fig.3 The Gripper.

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VII. References :

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