

# UNCERTAIN MOTOR PLANS LOWER STABILITY OF CURRENT PREHENSILE BEHAVIOR

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## INTRODUCTION

Ensuring the stability of motor action is critical for executing successful movements. However, maximizing stability is not always desirable [1]. For example, a transition between motor states must be preceded by the destabilization of the prior state. *Anticipatory synergy adjustments* describe the destabilization of a motor state that begins ~300 ms before the intended change in that state is observed [2]. Similarly, when rapid movement is expected in the near future, the motor system must manage two contrasting objectives: (1) ensure the stability of the current state, and (2) achieve rapid transitions to new states, if required. We argue that the stability of the current motor state is modulated to lower values to account for uncertain task requirements and to achieve dexterous task switching.

Here, we verify if stability modulation enables the dexterous use of the fingers. Subjects performed four-finger, isometric, constant force production tasks in two conditions. In the first (stable) condition, subjects produced one constant target force and had a-priori knowledge of the target's invariance. In the other (dexterous) condition, subjects tracked a longer, unknown, randomly varying trajectory that included the constant-force target as an integral part. We hypothesize that the stability computed during the constant force-production phases in the two conditions (1) will be maximal for the stable condition, and (2) will be progressively lower as the task demands increase.

## METHODS

Twenty-five healthy subjects (6 male, 20.4±2.5 yrs) participated in the study after providing informed consent. Subjects were seated comfortably in a chair with their forearms resting on top of a table. They placed the distal phalanx of each finger of their

dominant hand on one force transducer (Nano-17; ATI Automation). The transducers recorded each finger's downward vertical force at 1000 Hz. Visual feedback on the total force,  $F_T$ , was provided for all trials via a computer screen placed in front of the subject.  $F_T$  was computed as the sum of the vertical downward forces of all fingers ( $F_T = \sum F_i$ ;  $i=1$  to 4).

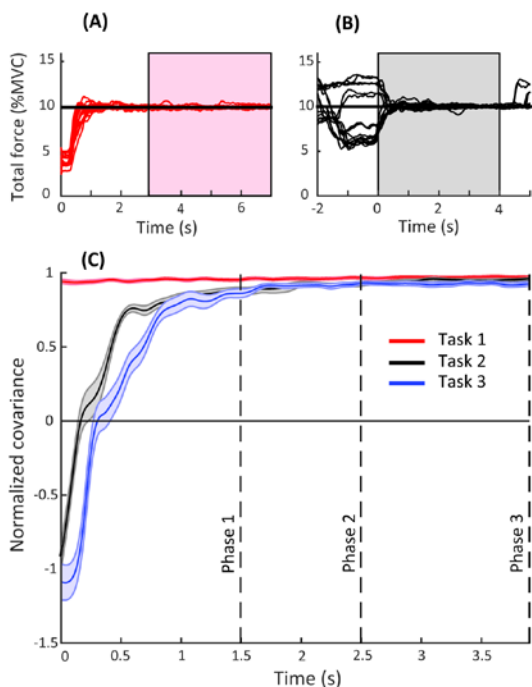
For the stable condition (Task 1), subjects produced a constant  $F_T$  value (10% of maximum voluntary contraction - MVC) for 7 s with the knowledge of the target's invariant location. This task was repeated 16 times [2]. For the dexterous condition (Tasks 2 and 3), the subjects modulated their total finger force and tracked an  $F_T$  target that randomly changed its vertical position on the screen. The target  $F_T$  profiles lasted for 30 s and consisted of smooth transitions between varying durations and magnitudes of constant  $F_T$ , including one instance of 10% MVC which lasted for at least 4 s. There were 8 distinct target  $F_T$  profiles for Tasks 2 and 3 each, which were repeated once to obtain a set of 16 trials for each task type. The target moved faster for Task 3 compared to Task 2, making Task 3 harder. The trials were randomized within each task, and the tasks were block randomized across subjects.

The last 4 s of Task 1 (Fig. 1A), and the first 4 s of Tasks 2 and 3 were used for further analysis, after the data were time aligned to match the start of the 10% MVC portion (Fig. 1B). The individual finger forces ( $F_i$ ) were filtered using a zero-lag, 4<sup>th</sup>-order, low-pass Butterworth filter (10-Hz cut-off). At each time instant,  $t$ , the across-trial covariance in the finger forces was computed as the negative difference between the sum of variances in  $F_i$  and the variance in  $F_T$  and then normalized by the sum of the variances in  $F_i$ :  $C_N(t) = -[\sum(\text{Var}(F_i(t))) - \text{Var}(F_T(t))] / \sum(\text{Var}(F_i(t)))$ . Note that  $C_N > 0$  indicates negative covariation (*synergy*) in the finger forces. This is observed during the stabilization of the total

force: If one finger force increases, others compensate by reducing their force to maintain the total force. Conversely,  $C_N < 0$  implies positive covariation among the fingers and that the total force is destabilized [3]. Thus, greater  $C_N$  indicates a stronger synergy and greater stability. The  $C_N$  values were sampled at three *Phases* (1.5 s, 2.5 s, 4 s; Fig. 1C) and subjected to a two-way, *Task*  $\times$  *Phase* repeated-measures ANOVA (3 levels/factor). Bonferroni corrections were used for pair-wise comparisons.

## RESULTS AND DISCUSSION

The total force,  $F_T$ , in the 4 s window for Task 1 (Fig. 1A) shows fluctuations about the 10% MVC target. In contrast,  $F_T$  in the 4 s window for Tasks 2 and 3 (Fig. 1B) contain an initial period when force trajectories converge to the 10% MVC target from different previous states. Consequently,  $C_N$  for Task 1 displays a near-constant value, but  $C_N$  for Tasks 2 and 3 show a period (up to  $t \sim 0.3$  s) of positive covariation ( $C_N < 0$ ) that achieves  $F_T$  convergence to 10% MVC (Fig. 1C). Then, negative covariation in the finger forces gradually increases ( $C_N > 0$ ), reflecting an increasing tendency to stabilize  $F_T$ .



**Figure 1:** Representative data for Task 1 (A) and Task 2 (B). Data in the shaded rectangles is used for across-trial covariance analysis. Across-subject mean  $\pm$  SE of the normalized covariance (C).

The key observation is that  $C_N$  values for Tasks 2 and 3 always remain lower than those for Task 1.

ANOVA on the  $C_N$  values revealed main effects of *Task* [ $F_{(1,193,28.635)}=7.909$ ;  $p < 0.01$ ] and *Phase* [ $F_{(2,48)}=9.015$ ;  $p < 0.01$ ].  $C_N$  for Task 1 ( $0.962 \pm 0.006$ )  $>$  Task 2 ( $0.914 \pm 0.012$ ), and Task 1  $>$  Task 3 ( $0.891 \pm 0.023$ ). There was no difference between Tasks 2 and 3.  $C_N$  for Phase 1 ( $0.895 \pm 0.017$ )  $<$  Phase 2 ( $0.934 \pm 0.008$ ), and Phase 1  $<$  Phase 3 ( $0.938 \pm 0.013$ ). There were no difference between Phases 2 and 3. A significant *Task*  $\times$  *Phase* interaction [ $F_{(2,602,62.452)}=3.414$ ;  $p < 0.05$ ] indicated across-task differences:  $C_N$  change across *Phase* for Task 1 is minimal,  $C_N$  increases from Phase 1 to Phase 2 to Phase 3 for Task 2 and continues to approach the Task 1  $C_N$  value. However, for Task 3,  $C_N$  increases from Phase 1 to Phase 2, decreases from Phase 2 to Phase 3, and it is lower than the  $C_N$  values for Tasks 1 and 2 at Phase 3.

Our first hypothesis was supported by the data. The stability associated with the constant  $F_T$  is reduced ( $\sim 7\%$ ) when subjects expect to produce force changes of unknown direction and magnitude at an unknown time in the near future. Although the drop in  $C_N$  was similar for Tasks 2 and 3, it lasted longer for Task 3 (significant *Task*  $\times$  *Phase* interaction). These  $C_N$  changes are anticipatory synergy adjustments, but with two prominent differences: (1) they lasts over 8 times longer than the previously reported ( $\sim 300$  ms), and (2) we show limited destabilization that facilitates movement if and when required. In contrast, earlier work reports progressive destabilization of the current state that is necessarily followed by a state change in *self-paced actions* that do not involve uncertainty [2]. The relation between stability modulation and task performance remains to be established in our study. However, this is the first demonstration of task-specific stability modulation in hand function, and our results have implications for the understanding and the clinical assessment of manual dexterity.

## REFERENCES

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