

## VELOCITY-DEPENDENT TUNING OF MOTOR STRATEGY DURING 3D ARM MOVEMENT AND ITS RELATIONSHIP TO COMPOSITE COST FUNCTIONS

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The purpose of this study was to investigate the link between composite cost functions, within the framework of optimal control, and the velocity-dependent tuning of motor strategy observed during the control of unconstrained 3D arm movements. We considered an arm pointing task at three different speeds. Experimental results indicated a change of rotation axis for most subjects from the geometrical shoulder-elbow (SE) axis toward the minimum principal inertia (e3) axis as velocity increased. These findings were interpreted based on a numerical inverse optimal control approach, assuming a total cost composed of kinematic, energetic and dynamic elements. While the kinematic cost predominated at low speed, the contribution of energetic/dynamic costs was reinforced for speeded movements, likely to exploit the inertial properties of the arm.

**KEY WORDS:** speed-sensitivity, rotation axis, inertia, optimal control

**INTRODUCTION:** Understanding how the central nervous system controls 3D upper limb movements is a long standing issue in biomechanics and neuroscience. For instance, what variables are critically monitored during the performance of complex 3D movements such as baseball pitching or skilled overarm throwing, and serve as a reference for the brain to efficiently and consistently execute such motor tasks remain largely unknown. In particular, whether the non-visual control of the upper limb relies more on geometrical properties pertaining to the orientation of body segments and joint angles or on mechanical properties pertaining to the mass distribution and torques is still a matter of debate (Pagano & Turvey, 1995; Darling & Hondzinski, 1999; Wolpert et al., 1995). Interestingly, Isableu et al. (2009) showed that, during a cyclical arm rotation task, subjects exhibited spontaneous changes of rotation axis, switching from a geometrical one (Shoulder-Elbow axis, SE) to an inertial one (minimum principal inertia axis, e3) when executing the task at larger speeds. Hence, the reference variables used by the brain to control complex multi-joint movements might be speed-dependent.

Interestingly, the optimal control framework precisely makes hypotheses about the variables possibly represented by the brain for motor control (Todorov, 2004). We thus investigated the link between speed-dependent motor strategies and cost functions using biomechanical modeling and simulation within that framework. We hypothesized that the total cost function was composite and made of at least three types of representative components: kinematic, energetic and dynamic (Berret et al., 2011). Furthermore, the relative importance of these components of the total cost was sought for using numerical inverse optimal control (Mombaur et al., 2009, Berret et al., 2011). We predicted that the contribution of each cost component could depend on velocity and that dynamic costs could be favored during quick movements. Indeed, it is conceivable that the biomechanical significance of kinematic and dynamic factors actually depends on the speed of motion.

We thus designed a specific experimental protocol to investigate these questions, modelled the 3D arm dynamics, implemented inverse optimal control procedures and identified the composite costs underlying the experimental trajectories. We found a strong link between the speed-sensitivity of 3D reaching strategies and the relative contributions of the cost components, thereby arguing for a flexible representation of such variables within the brain during the control of skilled upper limb movements.

**MATERIALS AND METHODS:** Ten healthy subjects (5 women and 5 men) voluntarily participated in the experiment. Written informed consent was obtained from each participant

in the study as required by the Helsinki declaration and the local Ethics Committee. All of them were right-handed, free of sensory, perceptual and motor disorder, aged  $28 \pm 4$  years, weighted  $68 \pm 9.7$  kg and  $167 \pm 6.7$  cm tall and naive to the purpose of the experiment. The subjects were asked to perform pointing movements, from an initial upward hand position and L-shaped arm configuration [elbow angle  $90^\circ$ ; shoulder elevation  $90^\circ$  and external rotation  $90^\circ$ ] toward a horizontal plane. The task essentially consisted in a downward shoulder rotation, similar to Isableu et al. (2009). Subjects were instructed to move at three different speeds in a pseudorandom fashion (S=slow, N=normal, F=fast). Gaze was fixed and subjects were required to look at a reference point in front of them, preventing them from visually-guiding the movement. Importantly, no instruction regarding the final position of the fingertip on the planar surface was given to the participants in order to let each subject choose his/her preferred motor strategy as a function of speed. A motion capture system (Vicon motion system Inc., Oxford, UK) was used to record the 3D position of the upper limb at a rate of 250 Hz. A total number of 450 trials (15 trials x 3 speeds x 10 participants) were recorded and analyzed.

Movement parameters computed from the 3D kinematics were the following:

*Shoulder-elbow rotation indice (SE indice)*. The SE indice was defined as the mean absolute shoulder-elbow axis displacement. At each time step, the angle between the current shoulder-elbow axis position and its initial position (at  $t=0$ ),  $\alpha_{se}(t)$ , was computed and the SE indice was calculated as:

$$SE = \frac{1}{T} \int_0^T |\alpha_{se}(t)| dt \quad (1)$$

where T was the total movement duration. A strict rotation around this axis when performing the task was a possible strategy, which would yield a SE indice equal to zero.

*Minimum principal inertia rotation indice (e3 indice)*. The e3 indice is a dynamic parameter based on the minimum principal inertia axis displacement (denoted by e3). A method to calculate the instantaneous e3 axis for a 7-dof arm was described in Isableu et al. (2009). Importantly, it is worth noting that e3 definition only relies on the instantaneous arm configuration and its anthropometric characteristics. At each time step, the angle between the current e3 axis position and its initial position,  $\alpha_{e3}(t)$ , was computed and the e3 indice was calculated:

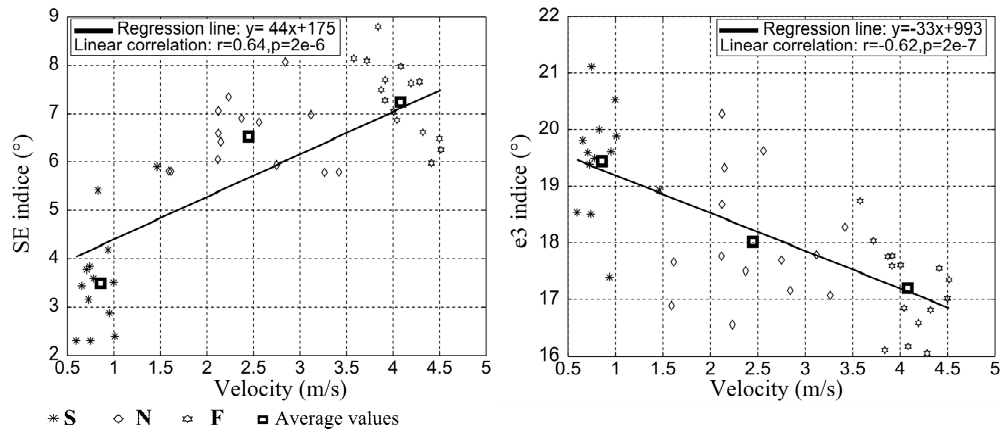
$$e_3 = \frac{1}{T} \int_0^T |\alpha_{e3}(t)| dt \quad (2)$$

A strict rotation around this axis was also a possible strategy, which would yield an e3 indice equal to zero.

*Inverse optimal control (IOC)*. To relate the above movement parameters to cost functions, we employed an inverse optimal control approach (Berret et al., 2011; Mombaur et al. 2009). The goal of IOC is to automatically uncover the composite cost function that predicts the best the recorded trajectories. In turn, this allows assessing the extent to which each cost component (here kinematic, energetic or dynamic; see Berret et al., 2011 for a precise definition of these cost functions) accounts for the observed arm trajectories. The latter quantity will be referred to as the *cost contribution*. Note that the description of 7-dof arm trajectories in terms of a few cost contributions is also a convenient way to describe complex 3D movements synthetically.

**RESULTS:** The evolution of SE and e3 indices with respect to speed (here peak of hand velocity) is displayed for a representative subject in Figure 1. A regression analysis was carried out from all the trials for each subject. ANOVAs were also conducted to examine the variation of the SE and e3 indices as a function of movement speed for each participant. The results revealed that a total of 8/10 subjects had significant correlations with positive regression slopes for SE indice (e.g. S3). ANOVAs revealed a main speed effect ( $p < 0.05$  for these subjects), meaning that the SE indice significantly increased with respect to speed. The two other subjects (S6 & S8) showed negative regression slopes and ANOVAs did not

reveal any main speed effect ( $p = [0.78, 0.77]$ ). Therefore, these two subjects could be considered as insensitive to variations of speed.



**Figure 1: Experimental SE and e3 indices for a representative subject (S3) as a function of peak velocity of the hand.**

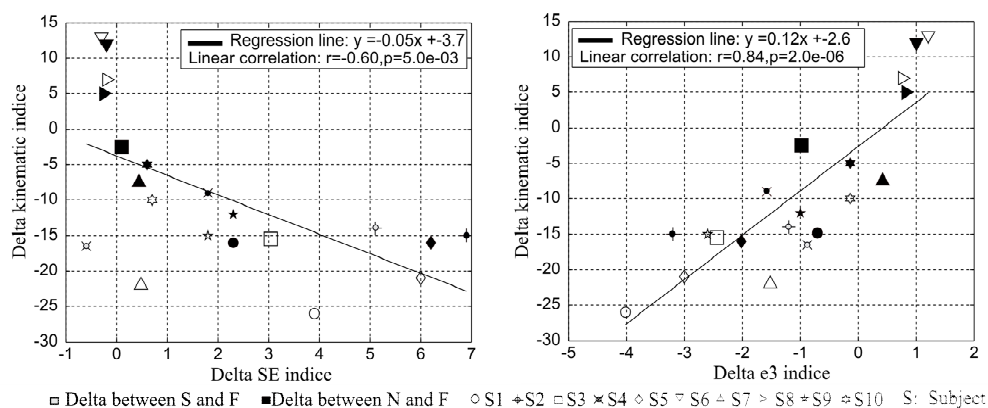
Similar observations hold for e3 indice. The same 8/10 subjects showed significant correlations with negative regression slopes (e.g. S3). ANOVAs revealed a main speed effect ( $p < 0.05$ ), meaning that e3 indice significantly decreased as a function of speed. The two remaining subjects showed positive regression slopes but ANOVAs only revealed a main speed effect S6 ( $p < 0.01$  for S6 and  $p = 0.4$  for S8). It should be noted that in any case the e3 indice was much larger than the SE indice (about  $18^\circ$  vs  $4^\circ$ ), illustrating that the motor strategy essentially involved rotations around the upper arm axis (but not strictly though). Indeed, fast movements tended to be associated with motor strategies making e3 axis more stable and SE axis less stable for a majority of subjects.

The link between the speed-related variations of those movement parameters and the changes in cost function contributions, as inferred from IOC, is depicted in Figure 2 for all subjects. Regression analyses were conducted to quantify the relationship between the relative changes of the above movement parameters with respect to speed and the corresponding relative changes of kinematic cost contribution. This inter-subject analysis showed that a velocity-dependent decrease of the kinematic cost contribution was found to accompany the velocity-dependent tuning of SE and e3 indices.

**DISCUSSION:** Our experimental results confirmed previous evidence for a velocity-dependent tuning of the motor strategy related to an exploitation of the inertial arm's properties, which becomes prominent at fast speed and turns out to alter significantly the 3D arm trajectories. These velocity-dependent changes were accompanied by changes of composite cost functions. In particular, the contribution of the kinematic cost to the total cost was diminished at large speeds in favor of an augmentation of its dynamic/energetic counterparts. Our results thus suggest that the speed-dependence of 3D arm reaching strategies could be partly explained by the presence of various components in the total cost, whose relative importance can be differentially revealed by movement speed variations. Therefore, the planning of arm trajectories may be done in both kinematic and dynamic coordinates (Wolpert et al. 1995; Isableu et al. 2009; Berret et al. 2011), with a weighting depending on motion speed.

From a practical perspective, our results thus suggest that advanced athletic tasks involving rapid and complex 3D arm rotations such as shuttlecock striking or overarm throwing could be related to motor strategies optimal with respect to more dynamical cost functions. The

optimal control strategies identified in experts (via inverse optimal control) could be used in turn to teach neo-practitioners how to better exploit the inertial arm's properties as well as all other passive sources of motion such as interaction or gravitational torques. Further studies are required to investigate more deeply the cost functions underlying expert sport movements, especially in tasks where objective costs related to accuracy and end-point speed are also present.



**Figure 2: Correlation analysis between the kinematic cost contribution and the SE (left) and e3 (right) indices. Only relative changes are depicted here (Delta) because the correlations were much stronger using a relative rather than an absolute approach.**

**CONCLUSION:** This study revealed a strong link between the speed-dependent tuning of 3D arm reaching movements and the composition of the underlying cost function. Our results suggested that skilled movements may flexibly rely on kinematic and dynamic/energetic variables depending on the task characteristics (e.g. speed) but also on individual factors (e.g. prior sensorimotor preferences). It would be interesting to extend these findings to expert's motion such as those involved in shuttlecock striking, baseball pitching or skilled overarm throwing.

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