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Characterization of action optimality criteria as a complementary assessment of pilot workload

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Abstract

Quantifying workload (WL) by physiological measures is not straightforward and few models exist to explain the mechanisms underlying it [1].
The aim of this study was to (1) identify the relationship between task difficulty (ID) and movement optimality (MO), and (2) compare kinematic criteria to subjective measures of WL.
The main results show that with increasing ID we observe (1) a modification in performance (2) the appearance of non-linearities in the kinematics, (3) a variation in white noise of the EMG signal. These results seem to validate the relevance of kinematic metrics as a marker of cognitive WL dynamics.

Helicopter steering is a very demanding task on the sensory-motor and cognitive levels, particularly due to the proximity of obstacles in the environment or some aerology situations (air movements, etc.). Pilots must constantly manage between steering performance and the cognitive cost induced by the difficulty of the task at hand. Consequently, the computational complexity of the steering task (sensorimotor and cognitive aspects) determines the workload associated with the different flight situations.

In aeronautics, the problem of the pilot's workload has been studied since the 1970s [2] through the evaluation of the flying qualities of aircraft, in which it is considered a determining criterion. Thus, the flying qualities of an aircraft are governed by a combination of four elements: (1) the aircraft (i.e. the response to the pilot's actions), (2) the pilot (i.e. the level of workload required to fly the aircraft in a specific task), (3) the difficulty of the task (i.e. the accuracy required in a given time) and (4) the environment (i.e. atmospheric disturbances, the presence of obstacles, the quality of the visual information). This combination allows us to define flying qualities as the ease with which an aircraft can be controlled by the pilot. This notion of ease is evaluated by the workload of the pilot when controlling the movement of the aircraft.

There are several types of metrics to assess the workload of an operator. They are mostly subjective through form such as the NASA-TLX, Cooper Harper. There are also behavioural measures such as the DIMSS-PM.

However, these metrics may have some advantages and limitations. In particular, subjective metrics may impose some constraints on their use and they do not specifically target the cognitive component. Indeed, if we take the example of the NASA-TLX form, it takes into account 6 very distinct factors ranging from the physical to the mental aspect to evaluate the workload (factors: physical, mental, frustration, performance, temporal, effort). These 6 criteria can be individually influenced by other factors (task, distraction, personality, psychological state...) and thus through the result which corresponds to the average of the scores of the 6 factors. Finally, they are only representative of a feeling at a precise moment and some of them require specific training such as the Cooper Harper for test pilots

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during aircraft certification. On the other hand, physiological measurements have the advantage of being continuous, objective measurements (based on the observation of human physics), thus allowing an evaluation throughout the task and not afterwards, which can bring more finesse in the measurement of workload. However, this type of measurement is more complex to implement, requires specific skills and there is still no consortium to validate the robustness of a physiological measurement compared to others [3]. Finally, in the aeronautical domain, there is the DIMSS-PM, which makes it possible to assess workload based on the pilot's control activity [4]. This measure is validated by the aeronautical community because it is easily applicable to some flight situations (particularly the landing phase). Nevertheless, it is not based on theoretical foundations of the understanding of action control mechanisms. Indeed, it is an empirical measure created for a specific landing task, which has limitations when the pilot has open loop control strategies [5].

It is in this precise framework that the contribution of a new metric for the quantification of the workload from the analysis of the activity on the handle makes sense to design an adapted assistance.

Indeed, it is possible to characterise some motor control mechanisms from the kinematic activity of the operator applied to the handle, in particular by means of motor control theories. This understanding is useful for the design of steering assistance functions. Thus, the evaluation of the quantification of cognitive resources from the stick activity seems to be relevant.

The aim of this study is to provide new measures of workload from the modelling, characterisation of motor control mechanisms observed from stick activity. This analysis is conducted by studying the relationship between task difficulty and movement optimality. We define optimality here as the way in which the nervous system manages a trade-off that allows for the performance of an action at the lowest cost.

Two hypotheses are formulated: (1) a decrease in movement optimality with an increase in task difficulty (i.e. presence of non-linearity in movement kinematics); (2) a monotonic relationship between movement optimality criteria and the subjective measure of cognitive cost.

2. Methods

2.1. Participants (inclusion/exclusion criteria)

8 right-handed male pilots (mean age = 32 years, SD = 8 years) participated in this experiment (i.e. >120h flight time). The exclusion criteria were: visual problems, neuromuscular problems and pathologies having a direct/indirect effect on the sensory-motor action. Following the Declaration of Helsinki, all procedures will be performed after each participant has signed a consent form. The acquired data are pseudo-anonymised.

2.2. Protocol

All participants performed the experiment with a positional control mode. Each experiment consisted of two distinct sessions, each characterised by a frame of reference (geocentric or egocentric) lasting 2.5 hours. For each experiment, the independent variables were the task difficulties (5 Indices of difficulty or IDs) and the reference frames (geocentric or egocentric).

The experiments were composed of two phases. The familiarisation phase, which allows the participants to become familiar with the task and to understand the functioning of the device (simulator, controller, task). This phase is validated after the participant has performed each of the 5 difficulty indexes (ID) +/- the necessary replay 3 times. The experimentation phase itself is composed of the 5 IDs. There are 8 blocks of the 5 IDs in a randomised order associated with each block. Each trial is characterised by an ID (previously defined following the equation of [6] the recommendations of [7]. During each trial, 30 targets are to be reached, i.e. 15 cycles/trial. A cycle is defined as a round trip: L-R-L. To validate a trial, the participant must achieve a percentage of success between 25% and 95% (i.e. pass the targets more than 7 times and less than 28 times). Each failed attempt (too many overshoots or undershoots) is replayed at the end of the series. For blocks 2, 4, 6 and 8, at the end of each trial, a subjective measure of workload will be taken using the NASA-TLX multi-criteria scale [8]. Finally, after each block of trials, the participants will be informed by the experimenter of the number of trials to be replayed.

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Table 1: Explanatory table for an experimental session

Pré-experiment	Explanations experience + Consent and image rights sheets	
Familiarization	(ID1 to ID5) x3 + Individual ID repeats	
Experimentation	Blocs n1 à 8 : (ID5 - ID2 – ID4 – ID1- ID3) + repeats	NASA-TLX for blocs 2, 4, 6 et 8.
Phases of the experiment	8 blocks of the 5 randomized IDs / 1 trial = 1 difficulty / Repeat for non-validated trials	

2.3 Experimental task

The proposed task is a reciprocal pointing task between two targets. The participant must perform the task via a controller in a mini-handle configuration (see Figure 1-C). The task consists of starting from a point centered between the two targets and then moving back and forth from one target to the other as quickly and accurately as possible (based on the principle of a speed/accuracy conflict). The speed instruction is given priority over the accuracy as it is classically done in the literature. At the end of every number 2,4,6,8 blocs, a subjective workload measurement is performed using the NASA-TLX multi-criteria scale.

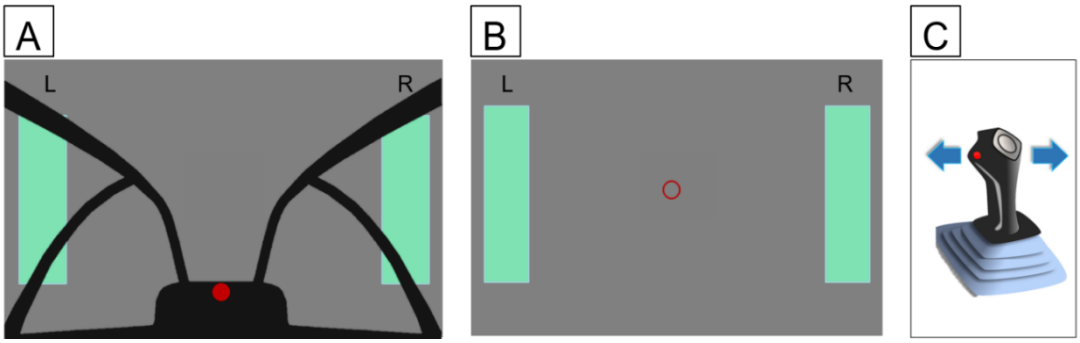

Figure 1: (A) Schematic of the experimental task in egocentric reference frame and (B) in geocentric reference frame with the annotations 'L' for left and 'R' for right on the targets represented by the green rectangles, (C) the controller with the blue arrows indicating the direction of the controller movement.

Table 2: Experimental settings for both repositories.

Difficulty Index (ID)	***Geocentric reference frame (target size in mm)***	***Calcul ID***	***Referential Egocentric (target size in mm)***	***Calcul ID***
ID1	160	3.13	200	3
ID2	100	3.81	100	4
ID3	70	4.32	70	4.51
ID4	40	5.13	50	5.32
ID5	25	5.81	25	6

2.4 Materials

For this experiment, we use the SCHEME experimental platform of Onera with an EC225 aircraft model, to which will be integrated: a Brunner® CLS-E Joystick (BRUNNER Elektronik AG), a Biopac®150 Systems, Inc. EMG device, with Acqknowledge 4.1® acquisition software (Software, Goleta CA 93117).
The virtual scene environment is realized via VESA. The kinematics is acquired at 100Hz by the simulator. In parallel, the models of each dynamic object of the system (i.e. aircraft, mini-handle, visual) are linked by the Simulink® software.

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2.5 Measurements

All measurements are made according to the type of movement (pronation vs. supination). The independent variables are the difficulty index, the control mode used (position) and the type of referential applied (geocentric vs. egocentric). The treated dependent variables are presented in Table 3.

Table 3: Presentation of all dependent variables

VD Task space	***VD Effector space***	***VD other***
-Number of validated targets	**Effector space kinematics**	- NASA-TLX
Task space kinematics	-Effector trajectory -Angular amplitude of sidestick -Temps de mouvement (TME)	
-Motion Time (TM)	**EMG**	
-Duration of the acceleration phase	- noise distribution EMG signal	
-Position of peak velocity		
		VD = dependant variable

Measurements in the space of the effector are also performed. The effector space (defined as the space of the participant's arm) will be the subject of kinematic and electromyographic measurements. Kinematic data from stick activity allows calculation of phase planes, Hooke portraits, velocity profiles, object motion time (TM), acceleration time (TAT), as well as the peak speed (PVT). The electromyographic measurements make it possible to calculate the level of co-activation and the PSD.

The electromyographic activity of the arm is recorded, synchronously with the simulation environment, at 2000 Hz with a gain of 500, on 6 muscles using a Biopac® 150 and electrodes (Vinyl 1-3 /8"Electrodes, stress gel; Biopac® Systems, Inc. Goleta, CA 93117).
The muscles of interest are:
- the medial deltoid and the posterior deltoid for the movements of the shoulder joint;
- the biceps brachii and the triceps brachii for movements of the elbow joint;
- the pronator teres and the brachioradialis muscle for wrist movements.

Each electrode is placed according to the recommendations of SENIAM. The skin of each subject is cleansed and shaved where each electrode is positioned. The reference electrode is attached to the lateral epicondyle. A start of test trigger is sent on the EMG recording from the start of the test (i.e. after the 10 seconds of stick positioning to initiate the task) as well as an end trigger when the last gate is crossed in order to synchronize the EMG recordings with the rest of the simulation.

Subjective workload measurements are obtained using the NASA-TLX scale [10] readapted into French by [8]. This scale is made up of six independent criteria that subjects must assess, on the basis of their feelings, on numerical scales.

2.6. Data analytics

Only the analysis of the data from the geocentric frame is presented here. Indeed, this case is more representative of real flight conditions and is the case best adapted to the explored hypotheses.

2.6.1. Kinematic data

The processing of the kinematic data is done by rigorously taking into account the size of the targets for each ID, which makes it possible to carry out the analysis only on the half-cycles (i.e. when the participant has crossed the two targets consecutively, i.e. here 27 half-cycles treated). The half-cycle represents in our case the passage between two successive pointings R-L or L-R which represents either a movement of supination or a movement of pronation.

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We analyze the data through a Python script. Previously, we filter the kinematic signal by means of a convolution with a Hamming window of size 11. Then we carry out the segmentation of the files from the start and end of test triggers, this allows us to recover one file per try (i.e. for each difficulty of each block). We then keep only the successful trials (i.e. having a success percentage between 25 and 95%) in each of the blocks. Then we averaged for each ID the 8 successful trials. We segmented each test by separating the portions of supination and pronation in 2 distinct variables, indeed we determined the moments of change of signs (positive/negative values) in order to delimit each half-cycle. All of these segmentations allowed us to calculate the following variables:

Phase plane (position vs velocity): it is a representation of the level of non-linearity of an oscillatory process. The phase portrait represents velocity according to position on a normalized circle [-1; 1], this criterion was introduced in [9] to show the evolution of the organization of the kinematic pattern of movement according to the constraints of the task.

Portrait of Hooke (position vs acceleration): it allows direct evaluation of the stiffness function [11]. Hooke's portrait represents the acceleration according to normalized position [-1; 1] is one of the criterion used in [9] to show the evolution of the organization of the kinematic movement pattern according to the constraints of the task.

Movement time (TM): it represents the average time over half cycles of the participant's hand movement. It is calculated from the angular position of the controller device (a Brunner mini-stick in this case) as the average time of two inverse movements.

Peak velocity position (PV): it is defined by the location of the peak velocity within a half cycle.

Acceleration Phase Duration (TA): this is determined by the time between the start of the half cycle and the peak speed.

2.6.2. EMG data

For the EMG data, we retrieve the signal from a trigger that marks the start of the simulator recording in order to synchronize the kinematic and EMG acquisitions. We analyze the signal by a Python script, where we rectified in absolute value, then filtered with a Butterworth band-pass filter (of order 6) 20-400Hz, followed by a Butterworth band-stop (of order 6) for frequencies between 49-50.5 Hz, then finally a 2nd order Butterworth low-pass at 50Hz. The normalization of the filtered signal is made in relation to the maximum contraction of each muscle per movement during the whole session. We consider a muscle as active when it was beyond 10% of the maximum over a minimum duration of 5ms. We remove the first two and last two cycles in order to analyze only the movement during the conflict and to minimize the effects of the start and end of movement impulse. From this signal processing, we analyze the EMG signal with Ervilha's co-activation index as described in [12]:

$$2*\frac{(EMG_{ANT})}{(EMG_{ANT}+EMG_{AG})} \qquad (1)$$

EMG_{ANT} = muscle activity of antagonist muscle
EMG_{AG} = muscle activity of the agonist muscle.

2.6.3. Subjective data

Data from the NASA-TLX form are averages of the 6 criteria. The first 3 dimensions are dependent on what the task imposes on the participant: the physical, mental and temporal demands; then the participant's interactions with the task: performance, effort and frustration.

NASA TLX analysis depends on the weighting indicated by the participant. This weighting makes it possible to know the weight of each of the 6 criteria. Then we multiply the value of the score obtained with the associated weighting.

During the NASA-TLX global analysis, weighted scores of each criterion were average for each ID for the entire block. Thus, we took for 1 criterion, we have an average of the 4 tests carried out on the 4 blocks. Then, we average all the criteria by ID.

During the NASA-TLX cognitive analysis, we take the same approach as the global one except that we isolate the mental criterion, and we do the same for the physical criterion.

2.6.4. Statistics

Statistical tests are applied to test the significance of the kinematic data and the electromyographic data through an R script. For this, we perform parametric statistics: repeated measures ANOVA, on the average of the validated

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half-cycles, the movement time of these half-cycles, the duration of the acceleration phase, the location of the speed peaks, the distance of the acceleration phase and this for each ID. Then, a Bonferroni post-hoc test is performed. Previously, the normality of the data was checked for a Shapiro-Wilk test and with a Greenhouse-Geisser correction. Finally, descriptive statistics are made.

3. Results

The performance (i.e. number of validated targets) is significantly different depending on the ID ($F(4,28) = 17.52$; $p<.001$). The post-hoc test shows significant differences between the IDs (see Figure 11-A). In particular, the number of validated half-cycles decreases with the ID.

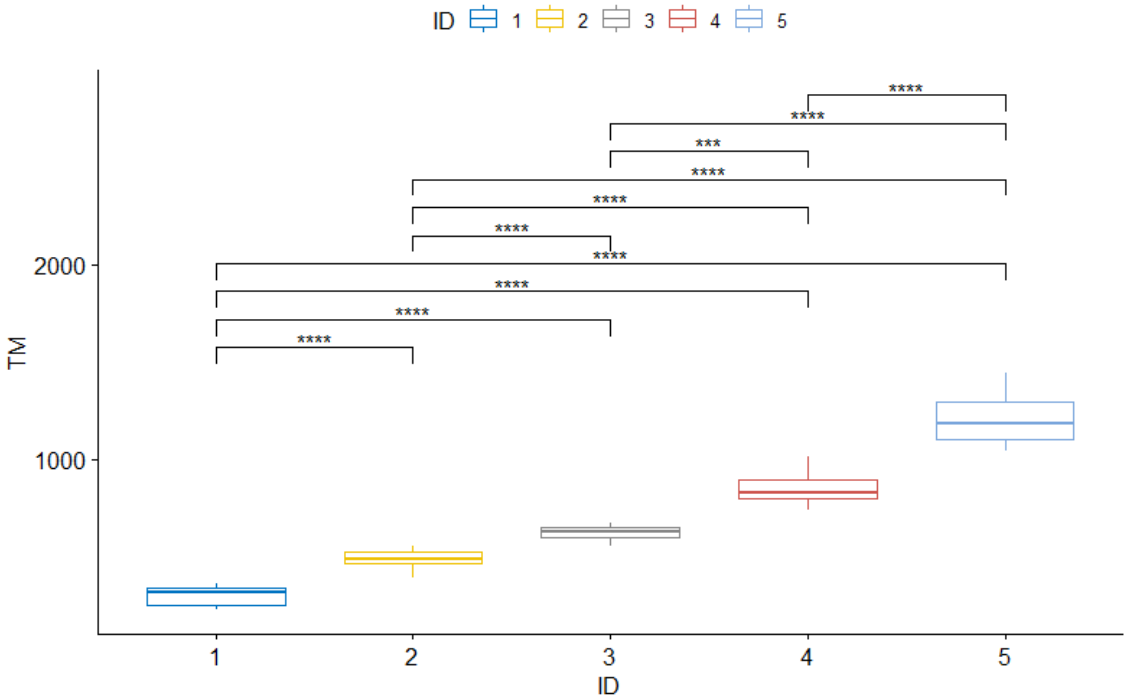

Figure 1: Movement time according to task difficulty with associated effects.

Movement time also denotes a significant difference between IDs ($F(4,28) = 341.2$, $p<0.05$ and $R^2 = 0.94$), with significant comparison differences between all ID pairs (see Figure 1). In particular, the movement time of the half-cycles increases with the ID.

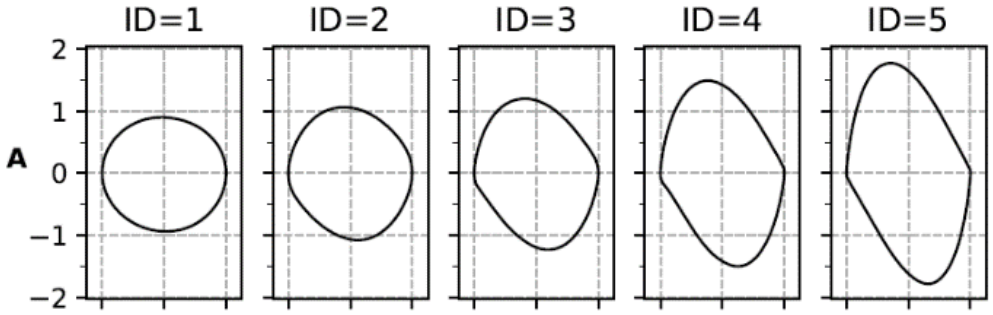

Figure 2: A-Phase plane (velocity according to position) normalized between 1 and -1 [9].

We can see on Hooke's phase and portrait plans a modification of the patterns with the increase in the difficulty of the task in accordance with the kinematic data such as duration of the acceleration phase, position and value of the peak speed, movement time.

The duration of the acceleration is significantly different between the IDs ($F(4.28) = 161.3$ $p<0.001$, see Figure 11-C) as well as the position of the speed peak ($F(4.28) = 395.3$, $p<0.05$, see Figure 11-D), peak speed value ($F(4,28) = 46.2$, $p<0.05$) and increases with task difficulty. For the position of the speed peak and the duration of the

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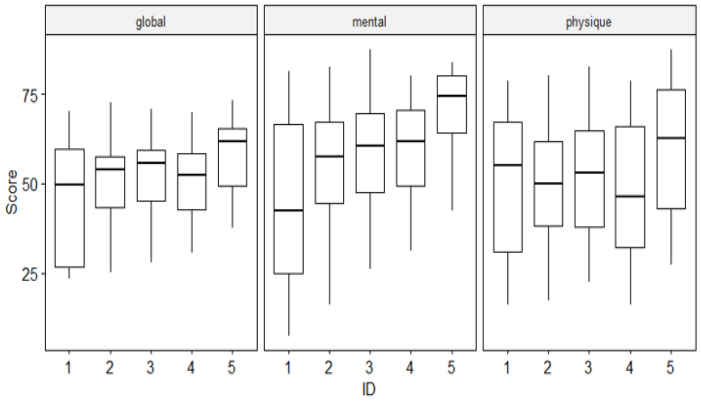
acceleration phase the post-hoc test shows significant differences between all the IDs except between ID3 and ID4 and ID5 respectively and between ID4 and ID5.



	Global	Mental	Physical	SD
ID1	45,703125	45	50	2,70670524
ID2	49,8697917	53,59375	49,0625	2,41701648
ID3	51,8489583	57,34375	51,40625	3,3076334
ID4	50,0520833	58,125	48,75	5,07868142
ID5	57,0833333	70,15625	59,6875	6,91950818

Figure 3: (A) Different NASA-TLX scores according to task difficulty. (B) Table of mean scores for all participants.

Finally, the scores obtained on the NASA-TLX form show a significant difference in the ID on the score of the forms $F(4.28) = 9.53$, $p < 0.01$ and a significant difference in the Type of score on the score of NASA-TLX with $F(2, 14) = 1.61$, $p<0.05$ and finally we observe a significant difference in the score according to Type and ID ($F(8,56)=4.28$, $p<0.05$). We also observe a significant effect of the ID on the 3 Types of scores, for the global score ($p<0.05$), the mental score ($p<0.05$) and physical ($p<0.05$). Also, we have specific significant differences for the ID4 between the global and mental score ($p<0.05$) and the ID5 for the global and mental score ($p<0.05$).

Also, we have a correlation between the mental score and the ID ($R^2= 0.36$, $p<0.05$).Concerning the relationships with the NASA-TLX scores and the ID, we have a significant correlation between the ID and the mental score ($R^2= 0.36$, $p<0.05$) whereas this relation was not significant between both the ID and the global score ($R^2 = 0.2$, $p >0.05$) and between the ID and the physical score ($R^2=0.12$, $p>0.05$). These results indicate that variation in ID primarily impacts the cognitive dimension of NASA-TLX.

Concerning the relation between kinematics metrics and NASA-TLX dimensions, we observe a significant relation between the movement time data and the mental score ($R^2= 0.35$, $p<0.05$), but not with the global and physical scores (respectively $R^2 =0.2$, $p>0.05$ and $R^2= 0.07$, $p>0.05$).

We also observe a negative correlation between the position of the speed peak and the mental score ($R^2 = -035$, $p<0.05$). Again, this correlation is not observed when considering the global and physical scores (respectively $R^2=-0.2$, $p>0.05$ and $R^2= -0.14$, $p>0.05$).

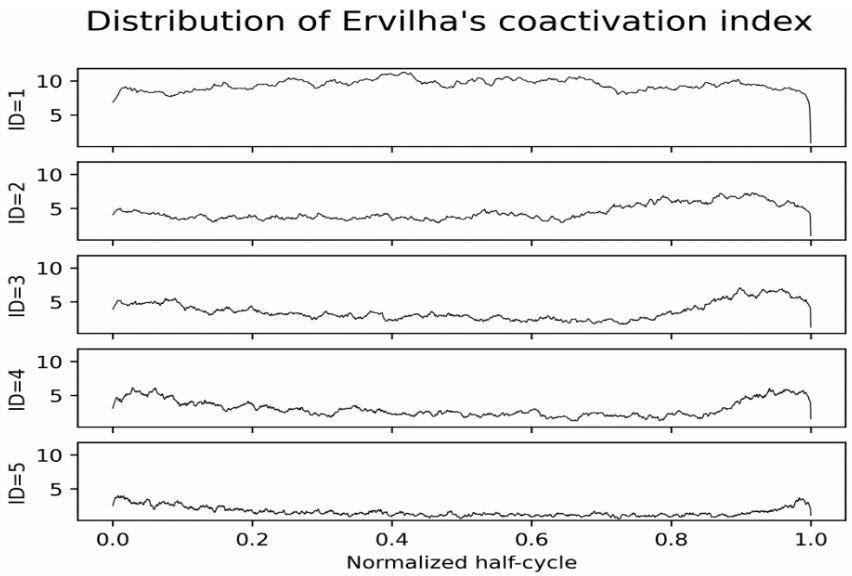


Figure 4: Distribution of the muscle co-activation index of the co-activation index for the couple biceps/triceps for all participants.

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Finally, we analyze the results of the distribution of the co-activation-index according to the difficulty of the task for the couple biceps/triceps (see Figure 4), and the two others couple of muscle. We see a variation in noise of co-activation with increasing difficulty.

4. Discussion

The objective of this study was to define new measures of workload from the characterization (1) of the optimality of action control for different IDs, (2) of the relationship between subjective measure of workload and criteria of optimality and action control performance.

The underlying hypotheses were: (1) a decrease in motion optimality with increasing task difficulty (i.e. presence of nonlinearity in motion kinematics); (2) a monotonic relationship between criteria of optimality of movement and the subjective measure of cognitive cost.

Our results show an increase in movement time with increasing ID, which allows us to validate the different parameters of our study (ID, W, D) and to observe that there is an impact of the difficulty of the task on performance. As a result, Fitt's law is verified for all of our participants with a deterioration in performance as the difficulty of the task increases.

[9] have shown that when the accuracy level of the task is high, a change in kinematic profile takes place by switching to a non-linear control mode. Indeed, they showed a change in the location of the velocity peak that arrives earlier in the movement (i.e. a shorter acceleration phase and a longer deceleration phase). a shift towards a fixed-point profile. This stable state in limit cycle is characterized by symmetry between the two half-phases of the reciprocal movement, with a peak of speed located at the center of the movement, synonymous with stability and fluidity of the movement. For the fixed-point profile, they found a shift in the peak velocity earlier during the acceleration phase and a greater deceleration with increasing ID, modifying the kinematic pattern of the movement. The behavior of this profile was studied by [13] who showed the appearance of two consecutive discrete movements separated by two reversal points. Thus, these studies determined that the behavior of the pointing movement was defined by a change in dynamics with increasing task difficulty and representative by a nonlinear dynamic model with specific characteristics. Other criteria show changes in the characteristic organization of kinematics depending on the constraint of the task, in particular the portrait of Hooke and the speed profile.

In our case, we can see a modulation of the kinematic patterns with the phase planes and Hooke's portraits. We find the switchover from limit cycle control mode to a fixed-point control mode, which is supported by the locations of the speed peaks and the duration of the acceleration phase suggest that the switchover. This new kinematic organization would seem to testify to the shift from reciprocal movements to the concatenation of discrete pointing movements when the difficulty of the task increases. Our results seem to show a modification of motor strategy with task difficulty through Hooke's phase set portrait plans. Thus, we can see an impact of the difficulty of the task on the optimality of the movement with a decrease in the linearity of the movement.

Furthermore, we note an increase in the overall NASA-TLX score with increasing task difficulty. Similarly, when analysing the mental and physical scores individually, our results seem to suggest the presence of a correlation between the mental score and the ID whereas the physical score seems to vary little with the difficulty of the task. We also have a negative correlation between peak velocity position and NASA-TLX scores, meaning that for a high peak velocity position we have a low workload score. Thus, we can say that when we have a low peak position value (i.e. arriving early in the half-cycle), we have a high workload, which is in agreement with the results of [9].Our results show a sensitivity of the optimality metrics that seems to be in line with the subjective measure of workload.

Finally, the distribution of the co-activation index for the biceps/triceps pair seems to show a variation in noise with increasing difficulty. In addition, [14] showed a variation of noise with the difficulty of the task. We need to complete our analysis to validate their hypothesis.

5. Conclusions

This experiment allowed us to (1) validate the optimality criteria and characterise their relationship with the difficulty of the task in the case of a geocentric reference frame in which it takes place and a positional control mode applied to the handle; (2) to validate the sensitivity of our criteria with respect to subjective measures of workload; (3) our current analyses do not allow us to validate an increase in the amount of noise in the distribution of EMG signal co-activation with increase, but do allow us to observe a modulation of noise with ID. In addition, we need to analyse the three muscle pairs and check for the presence of white noise as well as further spectral analysis.

These first results (geocentric reference frame, position control mode), allowed us to validate our criteria of optimality of movement (kinematics) to be used when evaluating the workload at the stick level, which can be used for the specification and evaluation of new piloting assistance functions. Indeed, a detailed understanding of the action control mechanisms and the criteria that characterise them is a crucial technical issue in the design of flight assistance

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systems. Indeed, this study validates the hypothesis that biomechanical criteria of movement can be used to quantify the cognitive workload.

Finally, further analysis of EMG signals and cost functions (such as minimum torque change) in relation to subjective measures of workload will provide further possibilities of biomechanical criteria for workload quantification.

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