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Exploiting the Link between Action and Perception: Minimally Assisted Robotic Training of the Kinesthetic Sense

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***Abstract*— Since action and perception are tightly coupled and the dysfunction of one of the two channels necessary give rise to different degrees of impairment in the other, we believe that the recovery process would significantly benefit from training protocols able to evaluate and consistently recruit both motor aspects and proprioception concurrently. Therefore, we propose a novel assistive protocol for kinesthetic training of reaching movements that is able to adaptively regulate the level of haptic guidance according to the level of proprioceptive performance along specific directions. Preliminary results show that our adaptive procedure is able to finely tune the level of guidance to the desired level of kinesthetic performance in all the target directions within the duration of the training session. Moreover, the algorithm is able to compensate for perceptual anisotropies that depend on the force direction and its parameters are sensitive to modulations of the kinesthetic sensitivity that may arise as a consequence of practice.**

I. Introduction

In recent years it has become evident that proprioception has a crucial role in promoting or hindering motor learning. In particular, it has been shown that an intact position sense following stroke strongly correlates with motor recovery of the hemiplegic arm [1]. Several studies highlighted the duality between motor and perceptual learning/adaptation [2]–[4] and in particular that addition of proprioceptive training can augment motor learning [5], [6]. Indeed, proprioception is essential for the correct calibration of motor commands. When visual feedback of movement trajectory is suppressed, variable errors in movement direction arise because CNS fails to take into account direction-dependent changes in inertial load during the planning phase [7]–[9]. Therefore in the absence of vision, movement execution is affected by directional-dependent biases due to the anisotropy of the arm impedance and the precision of joint angle proprioception is dependent on the configuration of the arm [10], [11]. Dually, our sensitivity to arm movements appears not to be isotropic with respect to the direction of the applied force [12]–[14]. These aspects need to be taken into careful consideration when designing experiments that make use of proprioception as the primary afferent channel.

The issue is even more critical in the context of robotic rehabilitation. When dealing with subjects with impairments it is fundamental to provide them with the correct amount of assistance to avoid overshadowing their volitional contribution to the targeted movement [15], [16]. Moreover, when conveying a haptic feedback, we often make the simplistic assumption that it is correctly interpreted by the subject the robot is interacting with and that the recorded performance is mostly dependent on the level of the subject's motor impairment. In general this is not true, since the two channels of action and perception are tightly intertwined. One of the open challenges is to implement effective and reliable tests and training protocols for proprioception that exploit the intrinsic bidirectionality of the kinesthetic sense, and take into account its properties.

To address these matters, in a previous work we have shown that a pulsed rather than a continuous force feedback can successfully comply with the requirements of a minimal assistive force paradigm in the case of chronic stroke survivors [17]. In order to quantify the volitional effort, we introduced a novel indicator called Active Contribution index (*AC* index) as a measure of consistency between the arm movement in response to the leading haptic perturbation and the direction of the force itself. Recently [18], we applied the same indicator to quantify the kinesthetic misjudgment in healthy individuals arising during reaching movements along five different directions on a plane and solely guided by a pulsed haptic feedback. Given the same amount of force acting along every target direction, the kinesthetic performance greatly varied as a function of the direction of the applied perturbation. In particular, targeted forces aligned with the axis of maximal mobility of the arm reported a significantly higher performance score when compared to directions rotated 90° clockwise. This discrepancy might underlie differences in

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the perception of the force impulse depending on its direction.

Grounding on our previous results, in this work we exploit the link between kinesthetic acuity and the *AC* index to design a new assistive protocol for kinesthetic training that is able to adaptively regulate the level of assistance according to the level of performance along a specific direction. The proposed algorithm is able to evaluate the *AC* index online and modulate the haptic feedback in time up to the minimum level of assistance necessary to reach the desired level of performance. This approach has several aspects of novelty. Firstly it allows to evaluate kinesthetic acuity in a directional manner, avoiding a psychometric estimate that is usually very time consuming and unpractical during a rehabilitation session. Secondly, the algorithm is able to automatically compensate for the intrinsic anisotropies in perception. Therefore, on one hand it warrants a uniform level of task difficulty over the span of reaching directions throughout the training session, on the other it is sensitive to modulations of kinesthetic sensitivity that may arise as a consequence of repeated exercise. Finally, it represents the first attempt to integrate active perceptual and motor training with an online quantitative evaluation of performance within the same exercise.

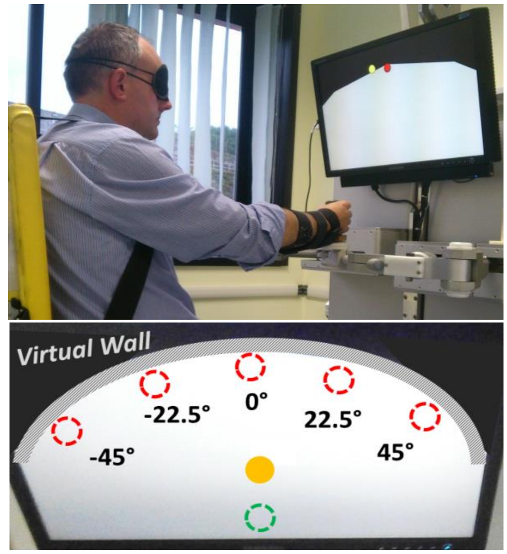

Figure 1. Top panel: experimental setup. Bottom panel: target distribution. The workspace is limited by a virtual wall (gray arch) that subjects cannot overstep. The red circles represent the mean target points for the 5 possible directions. The green circle represents the starting position. The yellow filled circle is the current hand position. The circles have a 2 cm diameter.

II. METHODS

The main goal of the proposed algorithm is to automatically identify the minimum force level necessary to achieve a predefined degree of kinesthetic performance during a reaching task in the absence of any visual feedback. Not only does the system detect this threshold force while performing the exercise by taking into account the directional anisotropy of perception, but it is also able to automatically track in time the possible modifications in the kinesthetic sensitivity that may arise throughout the training session as a consequence of the exercise.

A. Experimental Protocol

We provided haptic guidance and recorded the kinematics of the hand movement on the frontal plane by means of a robotic manipulandum [19]. The task required a blindfolded subject to identify and move towards the perceived direction of a force perturbation applied by the robot until reaching a target distance of 20 cm from a starting position, in which the hand was aligned with the shoulder joint. The hand grabbed a handle attached to the robot's end effector and the forearm was supported against gravity. A target was considered reached when the hand was closer than 2 cm and an acoustic feedback was delivered. After having performed an outward movement, the driving force always leaded the subject back to the starting point.

Previous to the beginning of the test, the subject's kinesthetic perception was evaluated via a two forced-choice discrimination test. The robot applied a sudden bell shaped perturbation of 200 ms of duration along a direction randomly rotated -45° or 45° with respect to the sagittal axis passing through the shoulder. The subject, blindfolded, had to answer if he/she perceived the hand to be displaced rightwards or leftwards. We applied a logistic regression to fit the percentage of correct answers as a function of the stimulus intensity and we computed the force corresponding to 85% probability of giving a correct answer, $F_{85\%}$. This value represents an estimate of the kinesthetic acuity during static conditions.

As for the evaluation in dynamic conditions, we explored five different force directions distributed 22.5° apart as shown in Fig. 1, bottom panel; 0° corresponded to the direction for which the hand was aligned with the shoulder center; the maximum angular deviation from the reference position was fixed to 45°. From now on, we will refer to leftward directions as negative angles, and rightward directions as positive angles. For each reference angle we identified three target positions: one centered on the desired direction and two at ±5° with respect to it. The target sequence was chosen pseudo-randomly so as to present every target only once every 9 reaching movements. A single target set was composed of 45 outward reaching movements (5 repetitions for target direction) and the whole session lasted 30 min for a total of 3 movement sets.

Visual feedback about the hand position was obscured by asking volunteers to wear a mask or to keep their eyes closed. The hand was subject to an assistive force field *A(t)* pulsed in time with a maximum amplitude F_{PEAK} and directed from the hand to the target point, a viscous contribution, and a very light continuous force that mitigated the bouncing-back effect of the force impulse. In addition, a virtual haptic wall centered in the starting position prevented the hand from going beyond 21 cm of distance. The net force $F(t)$ is represented in (1):

$$\begin{cases} F(t) = A(t) + C(t) - B\dot{x}_H - K_W(x_W - x_H) \\ A(t) = F_{PEAK} \cdot I_{\Delta t}(t) \dfrac{(x_T - x_H)}{\|x_T - x_H\|} \cdot R(t) \end{cases} \tag{1}$$

where $A(t)$ is the pulsed haptic guidance force field, always directed towards the target point, $\boldsymbol{x_T}$, B is the coefficient of the viscous field (12 Ns/m), K_W is the elastic coefficient of the virtual wall (1000 N/m), $\boldsymbol{x_H}$ the position vector of the hand and $\boldsymbol{x_W}$ its projection on the wall surface.

The impulse train is described in (2). The on-phase is characterized by a minimum jerk bell-shaped pulse of Δt = 200 ms duration. The off-phase duration is 300 ms, so that the train frequency is 2 Hz (T = 500 ms).

$$\xi = t/\Delta t$$
$$I_{\Delta t}(t) = \begin{cases} \dfrac{1}{1.875}\left[30\xi^4 - 60\xi^3 + 30\xi^2\right] & \text{for } 0 \le \xi < 1 \\ 0 & \text{for } 1 \le \xi \le T/\Delta t \end{cases} \tag{2}$$

The algorithm was evaluated on three healthy volunteers. Initially, we obtained an initial estimate of their kinesthetic sensitivity, i.e. $F_{85\%}$, during the discrimination test. This force intensity was used to initialize the impulse amplitude during the reaching test in 2 over 3 subjects. In the case of the third subject, the initial impulse amplitude was doubled with respect to $F_{85\%}$ in order to test for the effect of undesirable initial conditions on the algorithm behavior. In this case the number of movement sets was increased to 4.

B. Kinesthetic Performance Measure

The Active Contribution (AC) index exploits the pulsed nature of the guiding force field and measures the kinesthetic acuity as the degree of coordination between the movement executed during the guidance active phase with respect to the one immediately following the force impulse.

In designing the indicator, we assumed that the mismatch between the voluntary movement generated by the subject in response to the pulse and the direction of the force would have reflected inaccuracies in perception. This means that kinesthetic accuracy is inversely proportional to the angle between the force vector and the movement vector. Since the intensity of the motor response, i.e. movement speed, does not necessarily depend upon kinesthetic proficiency, we weighted the angular displacement in each impulse period by the ratio between the integral of the velocity vectors and the integral of the speed. This factor accounts for the deviation from straightness in the trajectory execution. The computation of the AC index AC_i over a single impulse period i is formalized in (4):

$$AC_i = \left\|\sum_{j=1}^{N_T} \vec{v}_j\right\| \Big/ \sum_{j=1}^{N_T}\left\|\vec{v}_j\right\|, \qquad S_i = \sum_{j=1}^{N_T}\left\|\vec{v}_j\right\| \cdot \Delta t \tag{4}$$

Where N_T is the number of samples in an impulse period and $\vec{v}_j$ is the j-th velocity vector. In the case of a perfectly straight trajectory, the velocity vectors are all parallel to the line joining the start position to the target one and the ratio between the two quantities is equal to 1. This value decreases if the path curvature increases, as the integral of the velocities would necessarily be inferior to the integral of the speed. In particular the score tends to zero if the subject does not provide any active focal motor command, as we may expect the small displacement determined by the force impulse would be followed by an almost equivalent backward displacement during the off phase.

The global AC index over N_p impulses is computed in (5) as the weighted sum of the partial scores over their relative contribution to the trajectory, i.e. S_i, penalized by the cosine of the angle between the force direction and the integral vector over the corresponding impulse period, α_i.

$$AC = \frac{\sum_{i=1}^{N_P} \alpha_i S_i \cdot AC_i}{\sum_{i=1}^{N_P} S_i}, \tag{5}$$

C. Adaptive algorithm for haptic guidance regulation

The goal of the proposed algorithm is to identify and track in time the minimum force $\overline{F}^j$ that allows for a desired kinesthetic performance along a specific direction j. The desired performance is quantified by the AC index value, and is referred to as $\overline{AC}^j$; the index k counts the number of trials along the j-th direction; the provided assistance level of the k-th trial along the j-th direction is identified by F_k^j, and the corresponding performance score by AC_k^j. At $k = 0$, the pulse force is selected equal to an initial guess $F_0^j = \hat{F}^j$ and the related performance score is quantified according to the AC index. At $k = 1$ the assistance level F_1^j is modulated to minimize the distance δ_0^j between AC_0^j and the ideal value $\overline{AC}^j$. In general, the force update policy at the k-th trial can be expressed as follows:

$$\begin{aligned} F_{k+1}^j &= F_k^j + \Delta F_k^j \\ \Delta F_k^j &:= \begin{cases} \delta_k^j \cdot \mu^j, & \text{if } AC_k^j > \overline{AC}^j \\ -\delta_k^j \cdot \mu^j, & \text{if } AC_k^j < (1-\varepsilon)\cdot\overline{AC}^j \\ 0, & \text{otherwise} \end{cases} \\ \delta_k^j &= \left|AC_k^j - \overline{AC}^j\right| \end{aligned} \tag{6}$$

where μ^j [N] is the step-size parameter and ε = 0.05 represents the lower tolerance bound on the desired AC index value. The role of the tolerance margin is to increase the robustness to the trial-to trial variability in the AC measure. The rationale is straightforward: if the delivered force F_k^j yields to a performance AC_k^j much lower than the desired one, it is very likely that the guidance level is insufficient and at the trial $k+1$ the stimulus will be increased proportionally to the mismatch between the desired and the actual performance; if the performance is above the threshold, the algorithm tries to attenuate the haptic guidance until the *AC* index becomes 5% inferior than the target one; if the performance is sufficiently stable, the force is unaltered and the training continues.

The time required for the algorithm to stabilize the stimulus value is critical, and it is necessarily limited by the duration of the training session. Moreover, since a certain amount of adaptation in time might occur [6], the algorithm should be able to respond promptly to changes in kinesthetic acuity in the course of the exercise. The two factors that strongly impact on the convergence speed are the step size μ^j and the initial force value $\hat{F}^j$. If the discrepancy between the initial guess and the force threshold is big, the choice of a high step size increases the responsiveness of the algorithm to the performance error but it may also cause an oscillating behavior around the threshold level. Conversely, a small step size allows for a finer exploration at the expenses of the number of trials, along with a higher risk of overestimating the force due to mental fatigue. Inter-subject differences in the sensitivity to stimuli close to the threshold make the choice of the step-size in the proximity of $\overline{F}^j$ very critical to reach to the equilibrium condition. The sharper is the kinesthetic response to the impulse intensity, the smaller should the step be around the threshold value.

To comply with the time constraints and the need for adaptation we implemented a reward-based learning procedure that modulates the step size throughout trials. Our objective is to regulate μ^j so as to balance exploration over the range of possible impulse intensities and the need for convergence. For instance, at the beginning of the training session, the step size should be high enough to allow for the algorithm to rapidly move in the direction of the threshold. When the threshold is approached, instead, the step should be reduced to track the small modifications in the sensitivity to the force.

Equation (6) describes a deterministic and memory-less policy in which the intensity of the pulsed force is modulated as a function of the current error over the kinesthetic performance. Since we aim at modulating the step-size parameter according to the performance in time, we applied a reward assignment to keep trace of the *AC* index values over a finite time window of *m = 3* trials for each direction. The window length allows for updating the reward depending on the mean performance over the three targets corresponding to each direction. Equation (7) describes the reward assignment policy.

$$w_n^j = \frac{1}{m}\sum_{z=0}^{m} r_{3n+z}^j$$
$$r_{3n+z}^j := \begin{cases} 1, & \text{if } AC_{3n+z}^j > AC_{3n}^j \\ -0.5, & \text{if } AC_{3n+z}^j < (1-\varepsilon)\cdot AC_{3n}^j \\ 0, & \text{otherwise} \end{cases} \tag{7}$$

where $3n + z = k$, and w_n^j is the reward score of the *n*-th time window. It can be seen from (7) that the assignment of rewards is asymmetric. In particular, considering a single time window *n*, trials in which the *AC* index increases weight more in the computation of w_n^j than trials in which the performance worsens. As we will explain in the following paragraph, a positive reward will increment the probability of reducing the step-size; this choice explicitly favors convergence over the exploration in time.

Let us define $\mu_0^j = 1N$ as the initial value of the step-size along the *j*-th direction, μ_n^j and $\Delta\mu_n^j$ respectively the step value and the step increment at the n-th update iteration. At the update step *n* the algorithm can select two opposite actions: either increment or decrement μ_n^j. The selection policy is based on a stochastic process in which the probability of taking one action is equal to its estimated value function considering the rewards w_n^j as in (8).

$$\begin{aligned} &Q_n{}^j(a) := (1-\alpha)Q_{n-1}{}^j(a) + \alpha(w_n^i + \gamma \max_a Q_{n-1}{}^j(a)) \\ &P_n^j(\mu_n^j > \mu_{n-1}^j) \sim U(0, \max_a\{Q_{n-1}{}^j(a), 1\}) \\ &P_n^j(\mu_n^j \le \mu_{n-1}^j) \sim U(0, 1 - \max_a\{Q_{n-1}{}^j(a), 1\}) \end{aligned} \tag{8}$$

where *a* represents the action of incrementing μ_n^j; $P_n^j(\cdot)$ is the probability of taking that action; $Q_n^j(a)$ is the action value; α = 0.3 corresponds to the learning rate and expresses how much the rewards affect the current value; γ = 0.5 is a discount factor that weights the influence of future vs current rewards. After updating the action values, the algorithm draws the action of incrementing μ_n^j with uniform probability in the interval 0 and $Q_n^j(a)$. The step-size value is then updated as in (9):

$$\begin{aligned} &\mu_{n+1}^j = \mu_n^j + \Delta\mu_n^j \\ &\Delta\mu_n^j := \begin{cases} 1.1\cdot\mu_n^j, & \text{if } a = \text{'increment'} \\ 0.9\cdot\mu_n^j, & \text{if } a = \text{'decrement'} \end{cases} \end{aligned} \tag{9}$$

We determined the value of the parameters *α* and γ by simulating the behavior of the model in the presence of a specific constant reward, given the initial conditions of Q_0^j = 0, and μ_0^j = 1N. In particular, given a constant reward of 1, we required the algorithm to reduce the step up to 95% on average after 2 movement sets (10 steps of update along each direction). Consistently, when considering a constant reward of -0.5, the algorithm should be able to increase the step value up to 50% within a movement set. Finally, given a reward of 0, the value of the step should be constant except for a random contribution of Q <= 30%, to allow for small fluctuations around the threshold. Our conditions were satisfied choosing *α* = 0.3 and γ = 0.5.

Summarizing, the whole procedure for the stimuli selection along a direction *j* can be outlined as follows:

Initialize $F_0^j = \hat{F}^j, \mu_0^j = 1\,\mathrm{N}$

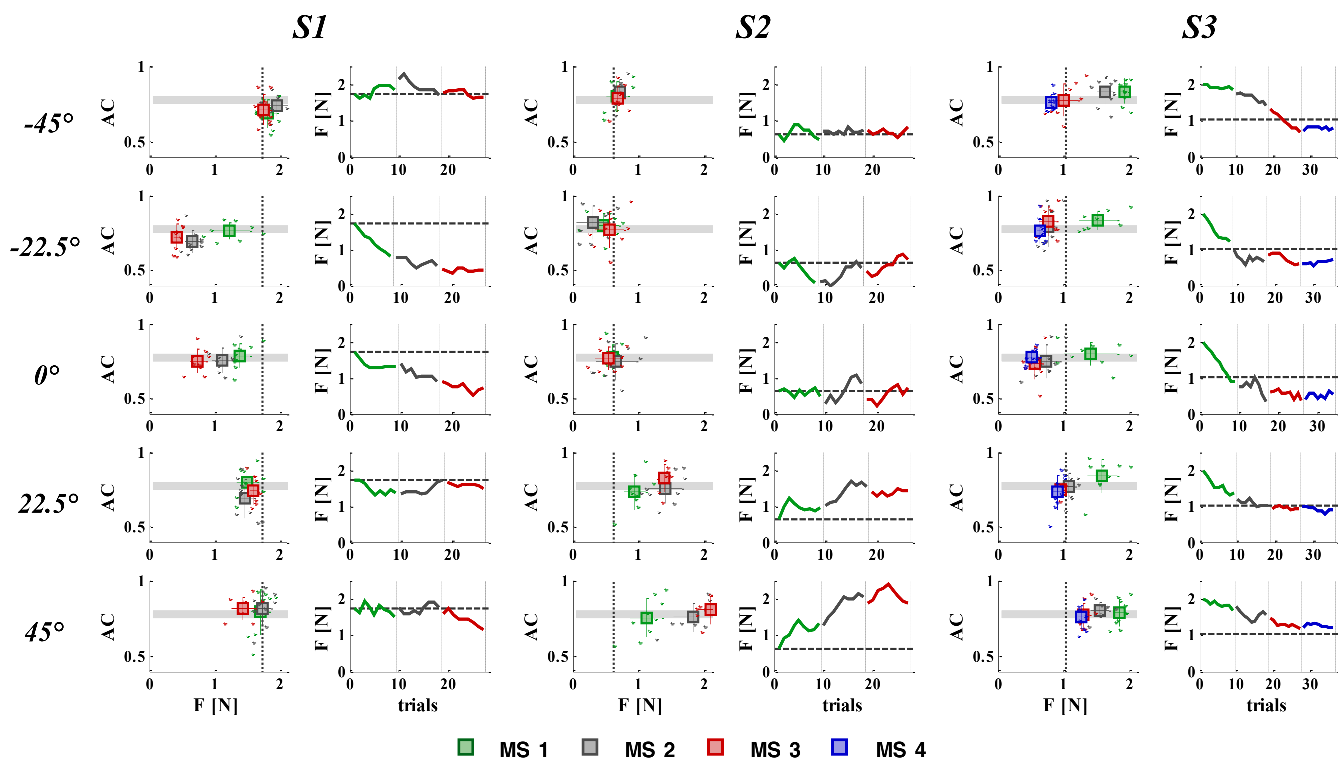

Figure 2. Measured kinesthetic performance as a function of the force stimulus (left columns) and the force stimulus amplitude throughout trials (right columns) for the three volunteers along the five target directions (rows); colors identify movement sets (MS); the gray area represents the interval of desired *AC* index values, $\overline{AC}^j \in [0.75; 0.80]$; the dotted vertical line represents the haptic guidance level in the first iteration, F_0^j.

FOR *each trial k in movement set*

Compute AC_k^j as in (5)

Compute δ_k^j as in (6)

Assign reward r_k^j as in (7)

IF *window n is completed*

Compute reward w_k^j as in (7)

Update action values $Q_n^j(a)$ as in (8)

Draw action *a* with probability $P_n^j(\cdot)$

Update step-size μ_k^j as in (9)

Update F_{k+1}^j as in (6)

III. Results

Fig. 2 shows the performance of the algorithm for the three volunteers that took part to the study. The first column represents the *AC* index values obtained in each movement set (MS) as a function of the peak force of the haptic impulse train, while the second outlines the evolution of the force stimulus amplitude over the trials with respect to $F_{85\%}$ (dotted line). In the case of S1 and S2 the initial F_{PEAK} value was set equal to $F_{85\%}$ estimated from the psychometric test (S1: 1.73 N; S2: 0.62 N). As for S3, the initial force level was fixed equal to the double of the estimated threshold ($F_{85\%}$ = 1 N, F_{PEAK} = 2 N). The left column panels of Fig. 2 highlight that the algorithm succeeded in tracking the desired performance: the average value of the *AC* index within the third movement set does not exceed the target region (0.77±0.04). Moreover, in all subjects the average force variability is reduced in time (MS1-MS3: -75%), independently of the distance between the initial force and the actual kinesthetic threshold. This occurred in association with a reduction in the update step size.

TABLE I. FORCE STEP SIZE FOR S3

MS	Final Step Size [N]				
	-45°	*-22.5°*	*0°*	*22.5°*	*45°*
1	0.80	0.98	1.46	1.20	0.98
2	0.64	0.78	1.50	1.17	0.96
3	0.57	0.57	1.32	0.77	0.56
4	0.37	0.37	0.87	0.68	0.37

TABLE II. PERFORMANCE PARAMETERS

Subject	Parameter	[N]				
		-45°	*-22.5°*	*0°*	*22.5°*	*45°*
S1	$F_{85\%}$	1.70	-	-	-	1.73
	F_{PEAK}	1.72	0.42	0.70	1.58	1.37
	AC	0.72	0.74	0.74	0.75	0.82
S2	$F_{85\%}$	0.64	-	-	-	0.69
	F_{PEAK}	0.69	0.62	0.57	1.38	2.14
	AC	0.78	0.76	0.74	0.83	0.83
S3	$F_{85\%}$	0.73	-	-	-	1.14
	F_{PEAK}	0.81	0.65	0.52	0.88	1.26
	AC	0.77	0.76	0.78	0.70	0.77

Table I reports the step size parameter value μ^j for S3 at the end of each MS along the five directions. The values tend to decrease moving from the first to the last MS and more dramatically for the directions j in which F_0^j was closer to the final force value.

Table II compares the level of guidance at the end of the exercise in the 5 directions (mean of the last 6 trials) against the $F_{85\%}$ estimate computed separately for stimuli along 45° and -45°. The final AC index corresponding to each direction and force is also shown. The values of $F_{85\%}$ that we computed separately for 45° and -45° directions were close to the final F_{PEAK} intensity in the corresponding direction in 2 over 3 subjects. The two values mismatched in the case of S2 along 45°. Considering the data in Fig. 2 together with the results of Table II, it is evident that the force direction strongly affected the kinesthetic performance. In particular, the kinesthetic acuity was greater for directions aligned with the forearm (-22.5°; 0°), where the inertial load is greater, while it almost doubled moving rightwards. These results support the hypothesis that the arm configuration plays a major role in the discrimination of force pulses direction [18].

The algorithm is also susceptible to variations of the force sensitivity threshold in time that might be due to adaptation phenomena or mental fatigue. Indeed, once the algorithm has converged to the threshold value, any modification in perceptual sensitivity would be mirrored by a modulation of the level of guidance through trials. This is the case for S1 along the 45° direction: the guidance level during the first two MS underwent only little fluctuations around the estimated $F_{85\%}$ value, whilst in the third MS it markedly decreases (-20%). Since the variation in the feedback intensity is accompanied by a reduction in the step size from 0.86 to 0.69, it is reasonable to assume that it is related to a decrement in the kinesthetic threshold.

IV. Discussion

The aim of the algorithm is to quantify the anisotropy in the arm kinesthetic sensitivity, i.e. the AC index, along multiple directions on a plane and to compensate for it by self-adapting the level of haptic feedback, i.e. F_{PEAK}. In this way, the amount of feedback information is modulated in time according to the proprioceptive performance, providing the CNS with an afferent signal of comparable intensity throughout the workspace.

Firstly, our results highlighted strong differences in the kinesthetic sensitivity as a function of the direction of the guiding force. In particular, the force threshold was lower along directions of minimal inertia for the arm, complying well with the hypothesis that kinesthetic sensitivity is affected by arm configuration and that anisotropies in perception are linked to the directional properties of arm inertia or impedance. How arm anisotropies influence our perception of force is a very interesting issue that deserves to be further investigated.

Secondly, the force estimated from the algorithm at the end of the session markedly differed from the one estimated by the preliminary discrimination test, which did not distinguish among multiple force directions. This result highlights the importance of having a sensitive measure of proprioceptive acuity that takes into account the intrinsic properties of kinesthesia.

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