Assessment of the visual noise influence on muscle activation during a tracking task

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***Abstract*—It is known how humans exploit their muscle contraction to increase the accuracy of their movements, in order to compensate for haptic disturbance or a combination of haptic and visual noise, but it is unclear the individual contribution of visual noise to muscle activity. Here, we aim to investigate the activation of the arm muscle during a 3-DoFs tracking task in presence of visual noise without any haptic feedback using a robotic interface. We evaluated four different levels of visual noise together with a no-noise condition. Tracking performance was assessed in terms of position and orientation error. An index of global muscle activation was obtained through data recorded with six EMG sensors placed on the participant's arm used in the tracking task. We observed that muscle activation decreased with the increment in visual noise for the first three levels. On the other hand, the muscle activation for the fourth noise level increased with respect to the third one, reaching values similar to the no-noise condition. As in previous studies, we obtained a linear relationship between tracking errors and visual noise with bigger errors corresponding to higher standard deviation values of the noise, while muscle co-contraction showed a more complex behaviour.**

***Index Terms*—Visual Noise, Muscle Co-Contraction, EMG Sensors.**

I. Introduction

To compensate for the variability affecting sensor information -referred to as *noise*- during motor actions, humans rely on both their prior knowledge and sensor information combining them through a *Bayesian integration* [1].

Previous studies revealed how *visual noise* affects motor task performance, showing that the higher the visual noise, the higher the error [2]–[4]. In addition, in [2] the relationship between the magnitude of the error and the noise (in terms of standard deviation) was found to be linear.

In [5] and [6], the authors exploited visual noise on the target to decrease the performance of one subject within a dyad executing a common tracking task and exchanging *haptic* information through a robotic interface. They found that the muscle co-contraction decreased in subjects with the visual noise, while increased in those who received an noisy haptic. These results pointed out the effect of the visual and haptic information (and their amount of noise) on the control of muscle co-activation. However, it is not entirely clear how the *visual noise* individually contributes to arm muscle contraction.

On the one hand, it is known that the central nervous system increases the limb impedance in case of a haptic disturbance, to achieve a higher task accuracy [7], [8]. On the other hand, the effect of only visual noise on muscle co-activation of the limb has not been investigated so far.

Here, we aim to study the influence of visual noise on muscle co-contraction without any haptic feedback. In particular, we evaluated the muscle activity during a three Degrees of Freedom (DoFs) tracking task involving five different levels of visual noise.

Four healthy participants were asked to perform a tracking task using a robotic interface. Depending on the visual noise level, the main target was replaced by a cloud of its replicas normally distributed with specific values of standard deviation.

We evaluated global muscle activation using electromyography (EMG) data, recorded from six muscles of the arm used to execute the task. For the sake of completeness, we analyzed also the tracking performance in terms of position and orientation errors depending on the visual noise applied, as did in the previous studies.

II. Materials and Methods

A. Experimental setup

During the experiment, participants sat in front of a monitor that provided visual information about the position of their cursor and the target (see Fig. 1). They controlled the cursor by moving a 7-DoFs robotic manipulator (Panda robot by Franka Emika) through an ergonomic 3D-printed handle fixed on the

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robot end-effector. The manipulator allowed only movements along the directions involved in the task (i.e. vertical plane movements plus rotation around the sagittal axis) being controlled with zero impedance in these directions and with high impedance along the other ones.

The coordinate systems of the robot and monitor are aligned, as well as the task one. In addition, the translation movements of the robot were scaled by a factor of two to allow participants to reach the full workspace on the screen with comfortable movements within arm range of motion.

The graphical interface for displaying the cursor and the target was developed in the Unity 3D environment through codes written in C# language. The software to control the EMG sensors and record the muscular data was implemented in C++ language. It exchanged information with Unity software through UDP communication about the position and orientation of the robot end-effector, displayed through the cursor pose.

The code for controlling the robot was implemented in C++ language using the Qt environment and Franka Control Interface libraries. While the EMG and the Unity software ran on Windows 10, the robot controller ran on Ubuntu 16.04 with a real-time kernel.

Data from the robot, graphical interface and EMG were recorded at 50 Hz, 100 Hz, and 1.1 kHz respectively.

Six EMG sensors (Trigno^{TM} Wireless System, Delsys) were employed to record the activity of Pectoralis Major, Posterior Deltoid, Biceps Brachii, Lateral Head of Triceps Brachii, Flexor Carpi Radialis, Extensor Carpi Radialis Longus (see Fig. 2).

B. Tracking task and visual noise

To assess how humans alter their arm co-contraction according to visual noise during movements, we asked participants to execute the tracking task used in [2]. It involved movements along the three dimensions indicated in Fig. 1: translation along the horizontal axis x; ii) translation along the vertical axis y; iii) rotation φ around the sagittal axis z.

Participants had to move their cursor through a robotic interface in order to track the position ($x(t)$ and $y(t)$ expressed in centimeters) and the orientation ($\phi(t)$ expressed in degrees) of a target following a multi-sine trajectory, as in [9]:

$$\begin{aligned} x(t) &= 3sin(1.8t) + 3.4sin(1.8t) + 2.5sin(1.82t) + 4.3sin(2.43t) - x(t^*);\\ y(t) &= 3sin(1.1t) + 3.2sin(3.6t) + 3.8sin(2.5t) + 4.8sin(1.48t) - y(t^*);\\ \varphi(t) &= 20sin(1.4t) + 12sin(2.5t) + 17.5sin(1.8t) + 8.1sin(2t) - \varphi(t^*); \end{aligned} \tag{1}$$

where x, y and φ represent target's position and angular rotation at each time t, respectively. $t = t_0 + t^*$, where $0\,s <= t^* <= 30\,s$ and the value of t_0 was randomly selected in the interval $[0, 10]\,s$ to avoid the memorization of the target trajectory during the experiment. The initial value of the coordinates ($t = t_0$ in Eq. 1) was subtracted from the trajectories to have the target starting with null coordinates at the beginning of each trial.

The center of the workspace corresponded with the screen one. The dimensions of the overall screen workspace are 26 centimetres for both x and y, and 110 degrees for the rotation φ.

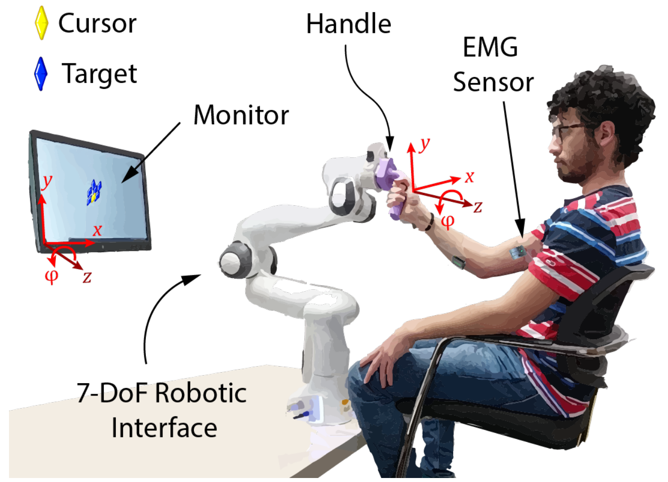
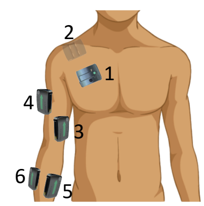


Fig. 1. Experimental setup. The subject seat in front of the screen, which is used to provide visual feedback about the target and the subject's cursor. The cursor is controlled through a 7-DoF robotic interface blocked in the directions not involved in the task and moved by the subject through an ergonomic 3D-printed handle fixed at the robot end-effector. Six EMG sensors are placed on the subject's arm and shoulder to evaluate the arm muscle contraction.



N°	Muscle	Role
1	Pectoralis Major	Shoulder Flexor
2	Posterior Deltoid	Shoulder Extensor
3	Biceps Brachii	Elbow Flexor
4	Lateral Head of Triceps Brachii	Elbow Extensor
5	Flexor Carpi Radialis	Wrist Flexor
6	Extensor Carpi Longus	Wrist Extensor

Fig. 2. Muscles recorded with the six EMG sensors. The activity of a flexor and an extensor has been recorded for each arm joint (shoulder, elbow, wrist).

The visual noise was applied displaying a cloud of ten target replicas instead of the main target. The position and the orientation of the replicas were normally distributed around the desired pose, computed using Eq. 1. To obtain different visual noise levels, the standard deviation of the normal distribution was manipulated in order to test four levels of visual noise together with the no-noise condition, in which the target is displayed sharp.

Table I shows the value of the standard deviation employed for each DoF in each noise level L. The computation of the Gaussian visual noise as well as the visual feedback updating was executed as described in [2]. For the sake of brevity, hereafter we refer to visual noise also as noise.

To evaluate muscle arm co-contracion, the activity of six muscles of the arm used during the task was recorded through EMG sensors. For each shoulder, elbow and wrist joint, we

TABLE I
VALUE OF STANDARD DEVIATION OF THE GAUSSIAN VISUAL NOISE FOR POSITION P AND ORIENTATION ϕ

	L0	L1	L2	L3	L4
σ_p [cm]	0	1	2	3	4
σ_ϕ [deg]	0	4	8	12	16

selected one flexor and one extensor muscle as reported in Fig. 2.

C. Experimental Protocol

Four healthy right-handed volunteers participated in the experiments (aged 31 years $\pm$ 5.7 years, one female) after signing a written informed consent. The experimental protocol was approved by the Ethics Committee of Università Campus Bio-Medico di Roma (HUROB protocol) and carried out according to the Declaration of Helsinki. To assess the handedness each participant executed the Oldfield test [10] at the beginning of the experimental session.

Initially, each participant executed a *Familiarization* phase consisting of one trial per each noise condition randomly presented, resulting in five total trials (four noise levels plus no noise condition). After the *Familiarization*, they were required to execute the *Task* composed of fifty total trials in which the four noise levels and the no-noise condition were randomly presented ten times each.

In both *Task* and *Familiarization*, trials lasted thirty seconds each and were followed by a resting phase of ten seconds to avoid the subjects' fatigue.

D. Data Analysis

To evaluate the task performance we used data recorded from the game (i.e. Unity software) to compute tracking errors along all the task DoFs (i.e. x, y, ϕ) as well as the euclidean distance in the xy plane. The root mean square of all the metrics was computed in each trial, and then for each participant, the mean values across trials with the same noise level was evaluated.

The recorded raw EMG data were filtered with a cascade of the following second-order Butterworth digital filters [11]: (a) band-pass filter in the frequency range $(20-450)$ Hz; (b) notch filter ($f_c = 50$ Hz); (c) low-pass filter ($f_c = 6$ Hz).

The average activity of each muscle M_i ($i \in 1, ..., 6$) in each noisy trial was normalized using the average activity recorded from that muscle in trials with no visual noise ($EMG^{Mi,L0}$) using the following relation:

$$EMG^{Mi,Lj}_{norm}(T_k) = \frac{EMG^{Mi,Lj}(T_k)}{EMG^{Mi,L0}}, \quad (2)$$

where $EMG^{Mi,Lj}(T_k)$ is the averaged EMG data in the k^{th} trial of the level j for the muscle i, with $j \in 1, ..., 4$ and $k \in 1, ..., 10$. Then, the normalized values of each muscle were averaged according to the visual noise level and finally, a global index was obtained as the average across all the muscles.

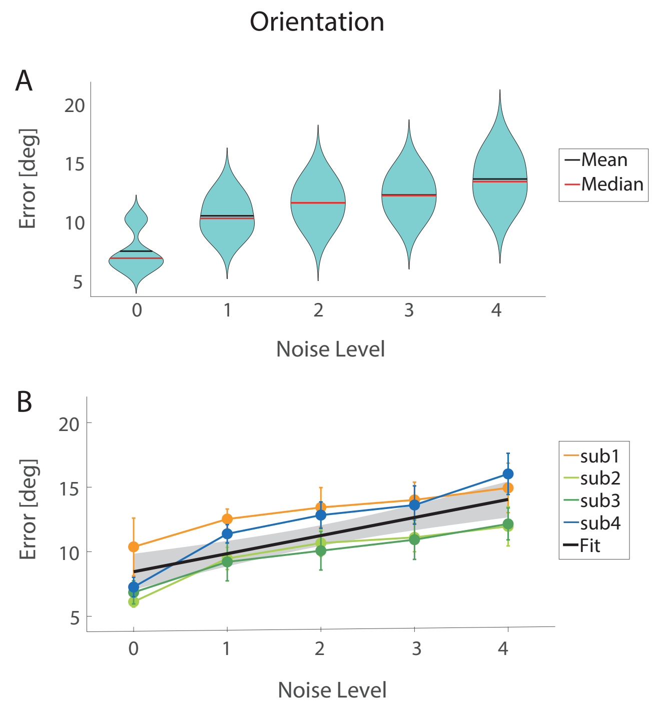


Fig. 3. Orientation Error. A) Violin plot describing the distribution of the orientation error of all the subjects (sub1 - sub4) with respect to the noise level. B) Orientation error of each participant (identified by colours) in each noise level. The black line and shadow indicate respectively the linear fit and the confidence bounds between the orientation tracking error and the visual noise (standard deviation).

The influence of the amount of visual noise on human performance was evaluated through a one-way RM Anova. We tested five levels (four visual noise conditions plus the no-noise one) in case of tracking errors, and four levels (the four visual noise conditions) for the muscle activation index. Indeed, in the latter case, the no-noise level was not considered since data were already normalized on that condition using Eq. 2. In addition, the values of muscle activation in each visual noise level were compared to 1 using a one-sample t-test to observe if the muscle contraction varied with respect to the sharp visual feedback.

III. RESULTS

As found in [2] and [3] a linear positive trend between tracking error and visual noise (standard deviation) is noticeable for both position and orientation errors (see Fig. 3 and Fig. 4) with the indices of the goodness of linear fit (R^2) respectively equal to 0.62 and 0.57 (Fig. 3B and Fig. 4B). The regressions were executed considering data of all the subjects since the Chauvenet's criterion did not show any outliers, even if the performances of one subject (sub1) are lower with respect to the other subjects.

Statistical analysis confirmed the main effect of visual noise on tracking error ($p < 0.001$) in all the evaluated indices,

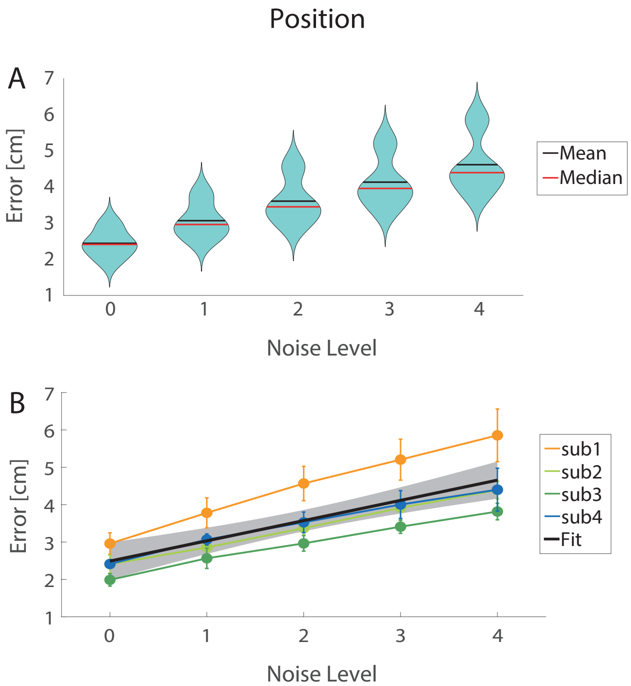


Fig. 4. Position Error. A) Violin plot describing the distribution of the position error of all the subjects (sub1 - sub4) with respect to the noise level. B) Position error of each participant (identified by colours) in each noise level. The black line and shadow indicate respectively the linear fit and the confidence bounds between the orientation tracking error and the visual noise (standard deviation).

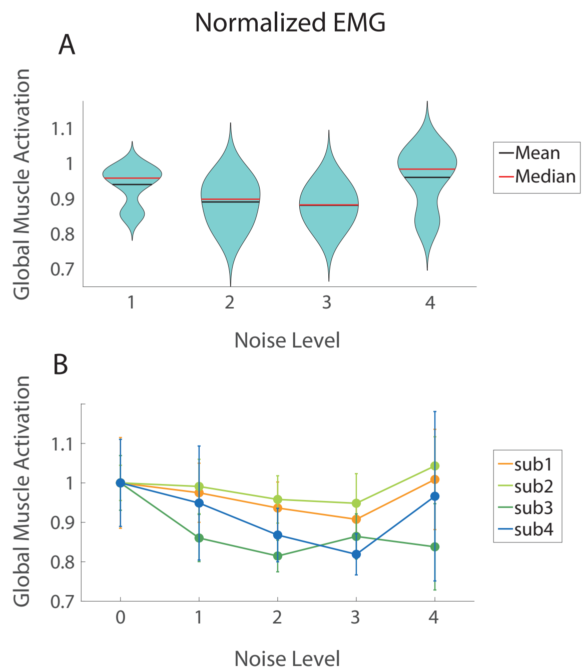


Fig. 5. Global muscle activation normalized by the mean value in no-noise condition. A) Violin plot indicating the mean and the median value among the subjects in each noise level. The highest median value is in correspondence with L4; L2 and L3 are statistically lower than the no-noise condition. B) Muscle activation trend among all the levels for each subject. All the subjects, except for the third, have similar trends: the activation decrease until the third level and increases in correspondence with L4. The third subject is the only one in which the highest value is in correspondence with L3.

with bigger errors corresponding to higher noise. Post-hoc comparisons with Bonferroni correction -for a family of ten comparisons- revealed significant differences among all the noise levels except for the comparison between L1 and L2 for the position ($p < 0.05$ for all the significant comparisons). Whereas for the orientation only L0 *vs* L4, L2 *vs* L3 and L2 *vs* L4 resulted to be significantly different being all characterized by $p < 0.05$. Table II shows the corrected p-values obtained for all the combinations among the noise levels, for position and orientation error, as well as for normalized EMG data.

As shown in Fig. 5A, the muscle activation decreased with the increase of the visual noise, except for the highest level in which it was on average higher than all other noise conditions. Table III shows in detail the mean and the standard deviation of the normalized muscle activation in the case of each noise level.

Although the one-way Repeated Measure Anova indicated a significant main effect ($p = 0.021$) of the noise level on muscle activation, the post-hoc tests with Bonferroni correction did not reveal any significant differences (see the *Muscle Activation* column in Table II).

At the same time, the one-sample t-test on the normalize EMG data, to compare the variation of the co-contraction with the value 1 (same co-contraction as the no-noise condition), indicated that in the case of L2 and L3 the muscle activity is lower than in condition L0 ($p = 0.024$ and $p = 0.013$ for L2 and L3, respectively). The increase of the muscle activity in the last level can be found in all the participants except the third one (Fig. 5B), whose muscle activity in L4 is comparable to L2 and L3.

TABLE II
P-VALUES OF POTS-HOC CORRECTED WITH BONFERRONI, FOR POSITION, ORIENTATION AND GLOBAL MUSCLE ACTIVATION.

Comparison	Position	Orientation	Muscle Activity
L0 vs L1	0.041	0.072	
L0 vs L2	0.045	0.062	
L0 vs L3	0.029	0.042	
L0 vs L4	0.030	0.069	
L1 vs L2	0.080	0.040	0.12
L1 vs L3	0.035	0.017	0.75
L1 vs L4	0.036	0.093	1.0
L2 vs L3	0.011	0.060	1.0
L2 vs L4	0.021	0.018	0.14
L3 vs L4	0.038	0.033	0.74

TABLE III
AVERAGE VALUE AND STANDARD DEVIATION OF THE GLOBAL MUSCLE ACTIVATION FOR EACH LEVEL OF NOISE, NORMALIZED WITH THE AVERAGE VALUES OF THE TRIALS WITHOUT NOISE.

Level	Mean	STD
L1	0.94	0.058
L2	0.89	0.066
L3	0.89	0.056
L4	0.96	0.090

IV. DISCUSSION AND CONCLUSIONS

Previous studies investigated the role of visual noise on human performance ([2]–[4]), the human strategy to control limb muscle co-contraction in the case of haptic disturbances only ([7], [8]), and that one in the case of a combination of haptic and visual noise in human-human experiments [5], [6].

In this study, we investigated how humans control muscle activation only as a function of visual noise during a 3-DoFs tracking task using a robotic interface.

We tested four different levels of visual noise, which were randomly presented to participants together with the no-noise condition.

We evaluated performance in terms of tracking error and muscle activity averaging the indices across participants, according to the visual noise level. Tracking performance indices confirmed the results of [2], indicating a significant influence of the visual noise on the tracking error for almost all the levels comparison, with a linear relationship between the noise standard deviation and the amount of error in both position and orientation movements.

We found that the average value of the muscular activation decreased with the increase of visual noise up to the third level, while in the highest values of visual noise (L4), it is higher than in the other levels and similar to the no-noise condition. Such behaviour can be observed in all the participants except one.

Although there is a significant influence of the noise level on muscle activation, there is no significant difference between levels, which can be due to the low sample size.

However, the trend of muscle activation among levels seems clear and it could be explained by a different perception of the visual noise according to its intensity. Indeed in the first three levels, the amount of noise could be seen by the participants as a reduced request of accuracy in performing the task, thus letting participants to follow the cloud of targets with lower accuracy with respect to a single sharp target. Conversely, the last noise level is probably high enough to be perceived as an actual visual disturbance.

Therefore, we suppose that in the case of levels L1-L3, participants perceived the accuracy required in the task as lower than level L0 and thus decreased their muscle arm co-contraction. Whereas, in level L4 the perception of the visual noise as a disturbance led them to increase their muscle co-activation in order to increase their accuracy, like in the case of force field disturbance ([8]) and human-human collaborative experiment ([5], [6]).

In order to better assess from a statistical point of view the effect of individual noise levels on muscle activity, future works will require an increased sample size. In addition, a further investigation of the effect of a high amount of visual noise on muscle contraction can be executed by changing the evaluation ranges of standard deviation. In this case, the focus should be on the region in which we observed the inversion of the trend and on highest values of noise with respect to the considered one (e.g. starting from L3 up to values higher than L4).

Finally, the modulation of muscle co-activation in the presence of visual noise can be assessed in the case of motor learning, in order to understand if humans adjust and optimize their limb rigidity according to the noise level, as observed in the case of adaptation to force fields.

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