Visual Noise Linearly Influences Tracking Performance

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***Abstract*— This study investigates the influence of visual noise on motor performance in three degrees of freedom (DoFs) tracking task including translation against gravity and rotation. Participants were asked to follow a moving target, visually degraded according to four different levels of noise, plus one no-noise condition. Each noise level was represented with ten target replicas normally distributed around the main target's pose with a specific standard deviation. Performance, in term of error between cursor and target, significantly decreased ($p < 0.001$) with the increase of the standard deviation of the visual noise, in all movement directions. The relation between the level of visual noise and the performance appears to be linear ($\mathbf{R}^2 > 0.8$) for each DoF separately, as well as when we combine the translations using the Euclidean norm.**

I. INTRODUCTION

While reaching an object or following a target, humans optimally combine sensor information and prior knowledge derived by the experience to generate motor outcomes [1]. This optimal combination has been suggested to follow a *Bayesian Integration* and it is adopted by the human brain to account for the variability that typically affects sensory information in order to reduce the error in the estimate of body position [2]. This variability of sensory information is typically referred to as *noise*, and it is of great importance to clearly assess how it affects motor performance [3].

Few studies showed that noise influences motor outcomes in different ways depending on its nature and location: noise on targets has a greater effect on performance than noise on feedback signals [4] and a visual degradation has more effect than visual intermittence [5]. Quantitative measures on a gaussian visual noise proved a significant decrease of the performance with the increase of the noise amplitude -in term of standard deviation- according to a linear trend [4].

Although these findings have been later used to modulate human performance in tracking tasks, simulating population of subjects with different motor skills [6], [7], they have been poorly investigated and limited to simple 1 or 2-Degrees-of-Freedom (DoFs) tasks. Moreover, the actual relationship between noise distribution and motor outcome has not been further analyzed.

A deeper knowledge on the relation between motor performance and visual noise may lead on one hand to a more accurate model of human behavior, and on the other hand to an easier and more precise modulation of human performance, simulating not only different levels of difficulty in the task but also different skills of the participants.

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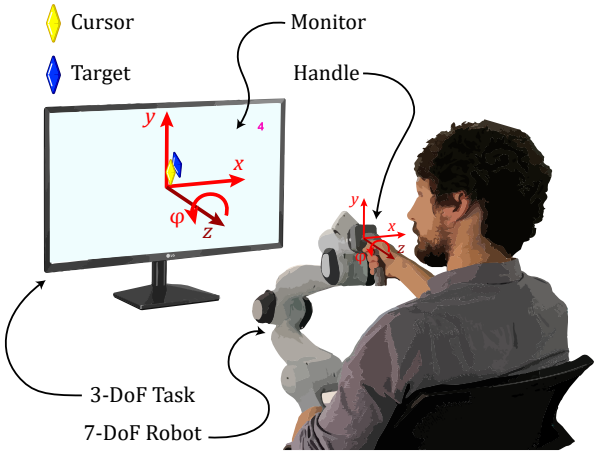

Fig. 1. Experimental Setup. A participant is seated in front of a monitor and moves the robotic handle to control the motion of the yellow diamond -*cursor*- following the blue one -*target*- with translations along the *xy* plane and rotations ϕ around the z axis.

In the present study we aim to quantitatively investigate the relation between visual noise and tracking error in 3-DoFs motor tasks, i.e. planar movements against gravity plus rotation, exploring also whether this relation changes among movement directions.

We asked six healthy volunteers to control a cursor following both orientation and position of a target moving on a vertical plane and rotating around the axis orthogonal to the plane. Different levels of visual noise were added to the target, by showing ten replicas of the target normally distributed around it. A 7-DoFs robotic manipulator was used to constrain the cursor (and participants' hand) movements only in the 3-DoFs involved in the task. The relationship between visual noise and performance -in term of tracking error along the 3 DoFs- was evaluated separately for each DoF, as well as combining the translations using the Euclidean norm.

II. MATERIAL AND METHODS

A. Tracking Task

To investigate how visual noise affects motor performance along different movement directions, we implemented a tracking task with three DoFs (see Fig. 1): i) translation on the horizontal axis x; ii) translation on the vertical axis y, i.e. against gravity; iii) rotation ϕ around the sagittal axis z.

Participants were asked to follow a moving target with their cursor, matching at the same time its position and orientation. They could control the cursor through a robotic

TABLE I

STANDARD DEVIATION OF THE GAUSSIAN VISUAL NOISE FOR POSITION AND ORIENTATION

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

interface, which constrained the handle to move in the three DoFs relevant for the task, whereas target moved according to the following multi-sine function [8]:

$$\begin{aligned} x(t) &= 6.4sin(1.8t) + 2.5sin(1.82t) + 4.3sin(2.43t); \\ y(t) &= 3sin(1.1t) + 3.2sin(3.6t) + 3.8sin(2.5t) + 4.8sin(1.48t); \\ \phi(t) &= 20sin(1.4t) + 12sin(2.5t) + 17.5sin(1.8t) + 8.1sin(2t); \end{aligned} \tag{1}$$

where x, y and ϕ represent target's coordinates in term of position and angular rotation at each time t.

Each trajectory had a duration of 30 seconds, starting from the initial time value t_0 randomly selected in the interval $t_0 \in 0 \div 10$ seconds. Target always started with null coordinates, i.e. we removed in each coordinate in Eq. 1 the corresponding value at time $t = t_0$. The overall target workspace, centered in the monitor center, ranges 26 centimeters for x and y and 110 degrees for orientation.

B. Visual Noise

Visual noise was rendered by replacing the moving target with a cloud of ten replicas [6] (see Figure 2), whose positions and orientations were normally distributed around the desired ones (i.e. the target pose computed with Eq. 1), with different values of standard deviation.

Four levels of noise plus a no-noise condition (L0) were tested (see Table I), each one characterized by a specific value of standard deviation for position (same value for x and y) and orientation, with standard deviation equal to zero being the no-noise condition (single target visible in Fig. 1).

At each time sample Gaussian distribution was implemented evaluating the position (n_x, n_y) and orientation n_ϕ of each replica through Box-Muller form, as follows [9]:

$$\begin{aligned} n_x &= R_p \cos(\theta_p)\sigma_p + \mu_x; \\ n_y &= R_p \sin(\theta_p)\sigma_p + \mu_y; \\ n_\phi &= R_\phi \cos(\theta_\phi)\sigma_\phi + \mu_\phi; \end{aligned} \tag{2}$$

where σ_p and σ_ϕ are the standard deviation values listed in Table I; μ_x, μ_y and μ_ϕ represent the desired coordinates x, y and ϕ of the single target at current time, evaluated according to Equation 1. R_k and θ_k, with $k \in \{p, \phi\}$, are computed from two uniformly distributed number u_k and v_k as follows:

$$\begin{aligned} R_k &= \sqrt{-2\ln(u_k)}; \\ \theta_k &= 2\pi v_k. \end{aligned} \tag{3}$$

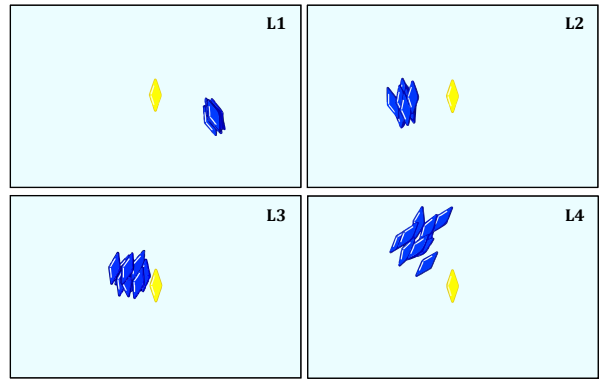

Fig. 2. Representative examples of four levels of visual noise. Target is replaced by ten replicas normally distributed in position and orientation, characterized by standard deviation values listed in Table I.

Visual noise was updated according to Eq. 2 and 3 each 400 ms [6], whereas target trajectory (see Eq. 1) was evaluated each 10 ms. To make smoother the visual rendering and account for the different frequencies, replicas' position and orientation were linearly interpolated between subsequent samples.

C. Experimental Protocol

Six healthy volunteers (3 women, aged 30.7 ± 6.9 years, all right-handed) participated in the experiment after having signed a written informed consent. Experimental procedures were approved by the Ethics Committee of Università Campus Bio-Medico di Roma (HUROB protocol) and carried out according to the Declaration of Helsinki.
Each participant performed fifty trials of thirty seconds each with a resting phase of ten seconds between successive trials. The four different noise levels and the no-noise condition (see Tab. I) were randomly presented resulting in ten trials for each noise level.

D. Experimental Setup

Participants were seated in front of a vertical monitor on which both a cursor and a moving target were displayed (Figure 1). A 7-DoFs robotic manipulator (Panda robot by Franka Emika) was employed -using an ergonomic 3D-printed handle- to constrain motions in the vertical plane and around the sagittal axis, i.e. the three DoFs involved in the tracking task. To this aim, robot control was implemented using zero impedance along the task directions and high impedance along the constrained ones. Robot movements were referred to the same coordinate system of the monitor (and the task). A scaling factor of two was used between the real and virtual translations to let participant spacing the entire virtual workspace with feasible arm movements.

Position and orientation data of both target and cursor were saved for each trial with a frequency of 100 Hz.

E. Data Analysis

Performance was evaluated in term of tracking error (i.e. difference between target - considering μ_x, μ_y, μ_ϕ in noisy

trials- and cursor poses in the task space) along each DoF involved in the task (i.e. x, y and ϕ). Additionally, position error was calculated as the euclidean distance in the xy plane between the target and the cursor.
All metrics were evaluated as root mean square value along each trial. To assess whether error linearly increases with the visual noise level -as suggested in [4]- a linear regression between error and noise standard deviation was executed separately for each DoF $i \in \{x, y, \phi\}$, according to the following relation:

$$SD|_{i,j} = a_i \cdot e_{i,j} + b_i, \tag{4}$$

where e_i is the error related to the ith DoF; SD is the standard deviation of the noise for the level $j \in 0 \div 4$ considering the values indicated in Table I; a and b are the regression coefficients. For each noise level, we considered the average error among ten trials for each subject.

Additionally, we normalized the average errors along x, y and ϕ dividing them by their corresponding average in the no-noise condition and then we used a RM Anova with *coordinate* and *noise level* as factors to test their effect on the tracking performance.

III. RESULTS

As first step we observed performance along each DoF separately. Figures 3-5 show the average tracking error for five participants, with respect to the noise level along x, y and ϕ coordinates. Additionally in Fig. 6 we reported the Cartesian position error combining x and y data. Even if reported in the bottom plots of Figs. 3-6, the values of one participant (sub6) were removed from the subsequent analysis since they showed to be an outlier according to Chauvenet's criterion.

The linear trend between noise and performance, suggested in [4], is immediately noticeable for all the DoFs separately, as well as for the position error, and it is confirmed by the goodness of the fit, with R^2 greater than 0.8 in any case. All coefficients and R^2 values of the regressions are reported in Table II. It can be noticed that slope values (represented by the "a" coefficient) along x, y and ϕ are almost the same. Bottom plots of figures 3-6 show also a graphical representation of the linear fitting between the errors and the standard deviation values (black line), superimposed to single participants' outcomes (colored dots).

Although one participant has been removed from the analysis, their performance represents an outlier only in term of errors' amplitude, but maintains the linear relation (R^2 equal to 0.99 for x, y and position and 0.87 for ϕ) between errors and noise (see red dashed lines in Figs. 3-6).

Statistical analysis on data normalized on the no-noise level values, confirmed a significant effect ($p < 0.001$) of the noise level on the tracking error, whereas the movement direction does not affect the outcomes. Post-hoc comparisons with Bonferroni correction revealed significant differences ($p < 0.001$) among all the noise levels, with higher noise levels corresponding to bigger errors.

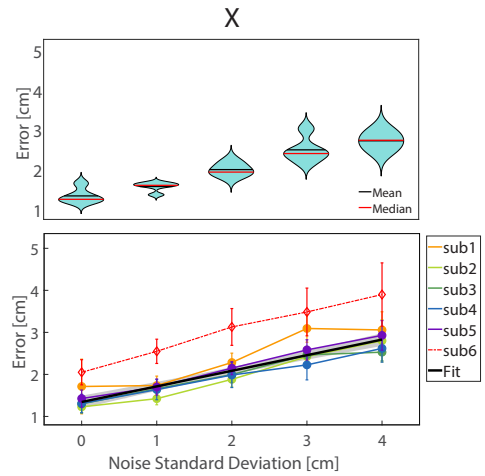

Fig. 3. Top: distribution of the errors of five participants with respect to the standard deviation values of the visual noise on the x axis. Bottom: in black (solid line and shadow) the linear fit and confidence bounds between tracking error and standard deviation value of the visual noise; data of five participants (colored dots) are fitted, whereas values related to the excluded subject are reported in red (diamonds and dashed line).

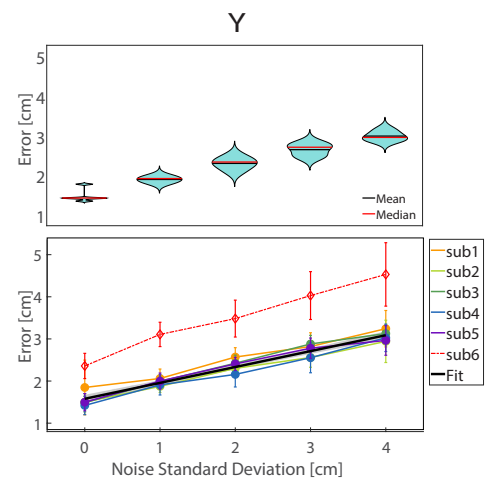

Fig. 4. Top: distribution of the errors of five participants with respect to the standard deviation values of the visual noise on the y axis. Bottom: in black (solid line and shadow) the linear fit and confidence bounds between tracking error and standard deviation value of the visual noise; data of five participants (colored dots) are fitted, whereas values related to the excluded subject are reported in red (diamonds and dashed line).

TABLE II

LINEAR REGRESSION BETWEEN THE ERROR AND NOISE STANDARD DEVIATION. R^2 INDICATES THE GOODNESS OF THE FIT, a AND b ARE THE COEFFICIENTS IN THE RELATION 4

	R^2	a	b
x	0.86	0.37	1.34 [cm]
y	0.94	0.37	1.52 [cm]
ϕ	0.83	0.42	7.58 [deg]
Position	0.93	0.53	2.09 [cm]

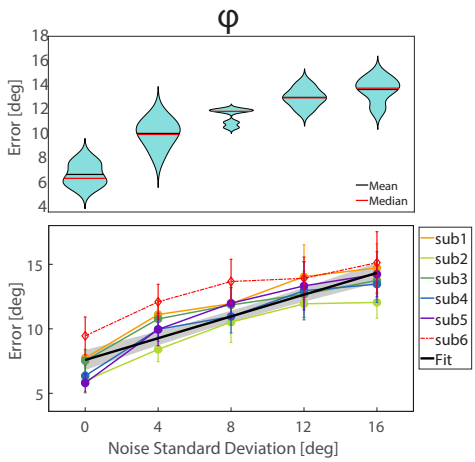

Fig. 5. Top: distribution of the errors of five participants with respect to the standard deviation values of the visual noise on the ϕ rotational angle. Bottom: in black (solid line and shadow) the linear fit and confidence bounds between tracking error and standard deviation value of the visual noise; data of five participants (colored dots) are fitted, whereas values related to the excluded subject are reported in red (diamonds and dashed line).

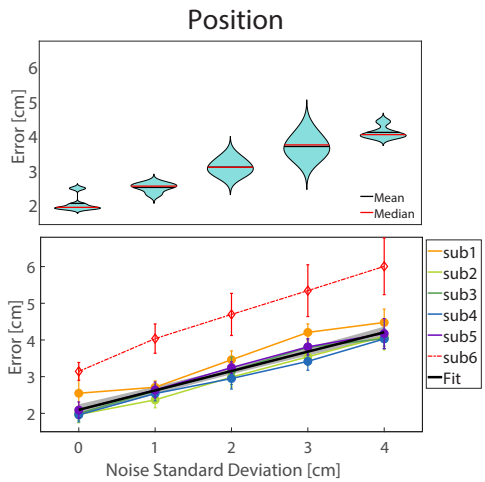

Fig. 6. Top: distribution of the errors of five participants with respect to the standard deviation values of the visual noise in term of position. Bottom: in black (solid line and shadow) the linear fit and confidence bounds between tracking error and standard deviation value of the visual noise; data of five participants (colored dots) are fitted, whereas values related to the excluded subject are reported in red (diamonds and dashed line).

IV. DISCUSSION AND CONCLUSIONS

In this study we investigated the influence of visual noise on motor performance in a 3-DoFs tracking task. Six healthy volunteers were required to follow the position and orientation of a target moving on a vertical plane and rotating along its orthogonal axis. We tested four levels of visual noise and one no-noise condition, by varying the standard deviation of ten target's replicas, distributed around the desired target according to a Normal distribution.

First of all we confirmed the results of [4], assessing the significant influence of the visual noise on the tracking error. Comparisons among the noise levels showed that the bigger the visual noise, the higher the error. Also, we found such effect regardless to the movement direction, i.e. along x, y and ϕ. Moreover, we tested the linearity of the relation between the visual noise and the tracking error, by means of a linear regression separately on the single DoFs, as well as considering the Cartesian error on the xy plane. All the regressions showed a high goodness of fit, with R^2 values higher than 0.8 in all cases and higher than 0.9 when involving the y axis. Further tests should assess if this result was due to gravitational effects on the arm movement. One participant was excluded from all the analyses being an outlier in term of errors amplitude, probably due to their motor skills worse than others even in the no noise condition. Nevertheless, despite the higher errors with respect to the other participants, they still maintained a strong linearity between errors and noise intensity along all task DoFs. Same results are obtained if motor performance is measured in term of position error, i.e. Euclidean norm of the difference between target and cursor position.

Summing up, motor performance is strongly influenced by visual noise of the target according to a linear relation between standard deviation of the visual noise and errors. This effect, as well as its linearity, occurs regardless to the motion DoF, irrespective of movements against gravity or rotations.

Results from this study allow to predict motor outcomes related to visual information, thus they can be adopted to further improve models about human motor control, e.g. the ones based on *Bayesian Integration*, but also to accurately modulate human performance in motor tasks.

Future works might investigate a wider range of standard deviations, to assess whether the linearity is maintained or some saturation effect occurs for huge amount of noise. Similar studies should be also conducted for assessing learning effects, as done by [3], to understand if and how the visual noise influence on motor performance persists over time and if it is affected by learning.

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