Controlling Hand Movements relying on Tactile Illusions: A Model Predictive Control Framework

Gemma Carolina Bettelani[1*], Simone Fani [2], Alessandro Moscatelli[3], Paolo Salaris[1], Matteo Bianchi[1]

***Abstract*— In recent studies, we demonstrated that when a blindfolded participant slides her/his finger-pad on a ridged plate to reach a target, tactile feedback induces the illusory perception of bending towards the direction perpendicular to the ridges. The contribution of tactile motion estimate is hence optimally integrated in a Bayesian way, with the estimate of muscular-skeletal proprioception and motor command. As a consequence, a systematic deviation of hand trajectories in the opposite direction with respect to the one estimated by touch can be observed. The goal of this paper is to exploit the aforementioned tactile illusion to guide the user's finger, moving on a ridged plate, towards an arbitrary desired point A, while she/he is instructed to move towards another target B. To this aim, we designed a Model Predictive Control strategy in a simulated environment to estimate at each time instant the optimal ridge orientation that minimizes a proper cost function. We simulated fifty trials for different positions of points A and B, also varying the level of the noise associated with the motor command and to tactile cue. Results show that the final positions of the simulated trajectories are in a range of $\pm 1.5^{\circ}$ with respect to the position of the desired final goal for $\sim 80\%$ of the cases. These results open promising applications in the framework of haptic retargeting where only one real object is used and the other items of the scene are virtual.**

I. Introduction

Haptic retargeting [1] is used in mixed reality environments to give to the user the illusory perception of reaching a virtual object, positioned in a certain place of the virtual scene, while she/he is reaching a real object positioned in another place with respect to the virtual one. The advantage of this technique is that the user can receive haptic feedback when she/he reaches different virtual items, using only one real object that is positioned always in the same location. Until now, haptic retargeting has been implemented manipulating the virtual environment through visual illusions [1]. However, to the best of the authors' knowledge, tactile illusions have not been exploited yet for haptic retargeting applications. This work aims at bridging this gap, which could lead to the creation of more immersive mixed reality environments while minimizing the usage of real objects.

[1] G. C. Bettelani, P. Salaris and M. Bianchi are with Research Center "E. Piaggio", University of Pisa, Pisa, Italy and with the Department of Information Engineering of University of Pisa, Pisa, Italy. {gemma.bettelani1} at gmail.com

[2] S. Fani is with the Research Center "E. Piaggio", University of Pisa, Pisa, Italy

[3] A. Moscatelli is with the Department of Systems Medicine and Centre of Space Bio-medicine, University of Rome "Tor Vergata," 00185 Rome, Italy, and also with the Laboratory of Neuromotor Physiology, Fondazione Santa Lucia IRCCS, 00142 Rome, Italy

* Corresponding author.

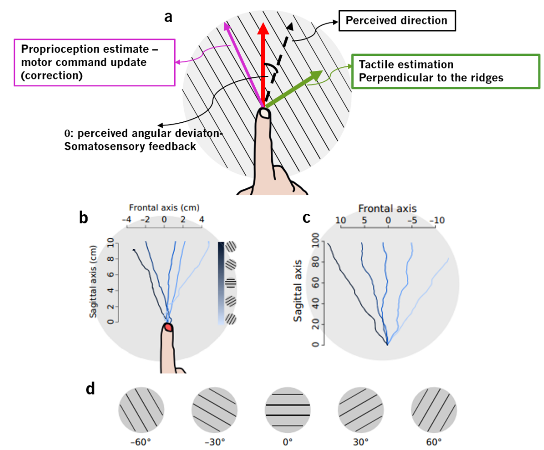


Fig. 1. a) When a participant moved the index finger on a plate with oblique parallel ridges, along the direction indicated by the solid red arrow, the cutaneous feedback produced an illusory sensation of bending towards a direction perpendicular to the ridges (dashed black line). This eventually led to an adjustment of the motion trajectory towards a direction opposite to the one arising from the estimate provided by the tactile flow (solid violet arrow). b) Trajectories obtained with a participant (different trajectory colors for different ridge orientations). c) Simulated trajectories with the Kalman filter for the different ridge orientations (same color code of (b)). d) Different ridge orientations used in [2].

In our previous studies [2], [3], we showed that touch provides auxiliary cues to guide hand movements. More specifically, we demonstrated that when a participant slides, without any visual feedback on hand location, her/his finger-pad straight ahead on a plate with oblique parallel ridges, the contribution of tactile cues on motion direction estimate induces the illusory sensation of moving perpendicularly to the ridge orientation. For this reason, the participant corrects the movement going in the opposite direction with respect to (w.r.t.) the one estimated by tactile cues (see Fig. 1 a, b). This illusion is still present when participants are instructed to move towards a virtual target, which is positioned with a certain orientation w.r.t. the mid-line of the plate, and visualized through a head-mounted display [2], as well as when the task is executed while the ridged plate rotates under the fingertip [4]. Therefore, if touch is an auxiliary cue for proprioception, then it would be reasonable to hypothesize that information from cutaneous and muscular-skeletal receptors on hand motion are integrated for hand motion estimation, in the reaching tasks previously explained. To formalize this hypothesis, in [2], we simulated trajectories at different ridge orientations using a Kalman filter model,

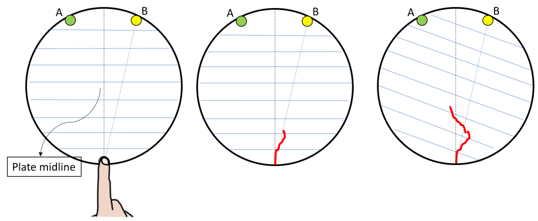


Fig. 2. On the left: the starting ridge orientation is set to $0°$. The finger indicates the starting position of the user. B ($-5°$ w.r.t. the mid-line of the plate) is the virtual target that the user has to perceive to reach and A ($5°$ w.r.t. the mid-line of the plate) is the real target that the user actually reaches. In the middle: the user moves her/his fingertip ahead towards target B (in red the trajectory). On the right: the MPC computes at each time instant the ridge orientation that has to guide the user towards the target A (in this case a clockwise rotation of the ridges that is considered a negative angular rotation of the plate)

which predicts the integration from the two different sensory cues. The results reported in [2], [4] show that the filter is able to reproduce the empirical findings (Fig. 1 c). Building upon these outcomes, in this paper we provide a solution to the problem of directing the movement of the user's finger to an arbitrary point A while eliciting the illusory percept of reaching a different point B. This can be done by dynamically re-orienting the ridged plate by means of a Model Predictive Control (MPC) strategy. In this manner, the participant should ideally perceive to move towards the instructed direction, but the controller guides him/her towards another desired direction. The results presented in this study have been tested in simulation, while additional work is required to apply this strategy with human beings. The findings of this work could open promising applications in the framework of haptic retargeting [1], [5]. Indeed, our control strategy could be used to guide the user's finger sliding on a ridged plate to reach the only real target in the scene, while the experimental instruction is to reach a virtual target placed at a different location. In this paper, we tested different positions for points A and B, changing also in simulation the noise associated with motor command and tactile cues. The results show that the final positions of the simulated trajectories are in a range of $\pm 1.5°$ with respect to the angular positions of the desired final goal for $\sim 80\%$ of the cases (of course it is important to stress the fact that user validation of this approach is needed to rule out limitations or errors in the models). The idea of exploiting tactile illusions using MPC for bending hand motions was presented in a very preliminary manner at the Italian conference: I-RIM 3D [6].

II. Materials and Methods

In this paper we propose a Model Predictive Control strategy to compute at each time instant the optimal plate orientation (i.e., it minimizes a proper cost function), to guide the user towards a desired point A, while she/he is instructed to move towards another point B (see Fig. 2). The optimal ridge orientation is computed considering at each time instant the output of the Kalman filter, which provides the estimate of the perceived motion direction based on tactile cues and muscular-skeletal proprioception. The Kalman filter model reported in the next section is taken from [2], but here it is presented with a different notation that we consider more straightforward for the implementation of the MPC strategy.

A. Kalman filter model

In [2], we introduced a Kalman filter model that estimates the perceived angular orientation of the hand (θ in Fig. 1 (a)), which is computed as an integration of the estimated direction from tactile feedback and the one estimated from classical muscular-skeletal proprioception (Fig. 1).

The dynamical evolution of the perceived angular motion direction, θ, can be defined in continuous time as follows:

$$\dot{\theta}_t = u_t$$

$$h_t = \theta_t$$

Discretizing the system with the Euler method, and considering a unitary time interval, we obtain (Fig. 3a):

$$\theta_{k+1} = \theta_k + u_k$$

$$h_k = \theta_k$$

where the symbols in the equations have the following meanings:

- θ_k: state of the system, angular direction of the hand perceived by the participant w.r.t. the mid-line of the plate (N.B all the angular directions are considered w.r.t the mid-line of the plate).
- u_k is the motor command, i.e., the motor action of the subject, who is trying to correct the possible deviation between goal and perceived directions.
- θ_{k+1}: model prediction of the direction perceived by the subject.
- h_k: output of the system equal to $\theta_k = w_T T_k + w_P P_k$ (measure of the somatosensory system).
- w_T: weight of tactile cues.
- w_P: weight of proprioception, equal to: $w_P = 1 - w_T$.
- T_k: contribution of tactile motion estimate, always perpendicular to the ridges, in accordance with the *Tactile Flow model* presented in [7]. In the task simulated in [2], the ridge orientation did not vary for the entire duration of the task, so this term was considered constant at each time instant.
- P_k: muscular-skeletal proprioception contribution. The proprioceptive cues are considered unbiased and equal to the participant's actual motion.

condition 1	$Real\ target$	$Virtual\ target$	ϕ
$\sigma_u{}^2$ = 0.5, w_T = 0.15	-5°	5°	94%
	5°	-5°	96%
	0°	10°	90%
	-10°	0°	94%
	10°	0°	96%
	0°	-10°	88%
condition 2	$Real\ target$	$Virtual\ target$	ϕ
$\sigma_u{}^2$ = 0.5, w_T = 0.1	-5°	5°	82%
	5°	-5°	80%
	0°	10°	80%
	-10°	0°	82%
	10°	0°	88%
	0°	-10°	84%
condition 3	$Real\ target$	$Virtual\ target$	ϕ
$\sigma_u{}^2$ = 1, w_T = 0.15	-5°	5°	78%
	5°	-5°	84%
	0°	10°	78%
	-10°	0°	80%
	10°	0°	82%
	0°	-10°	86%
condition 4	$Real\ target$	$Virtual\ target$	ϕ
$\sigma_u{}^2$ = 1, w_T = 0.1	-5°	5°	76%
	5°	-5°	72%
	0°	10°	80%
	-10°	0°	82%
	10°	0°	78%
	0°	-10°	79%

TABLE I

TABLE WITH ALL THE TESTED CONDITIONS

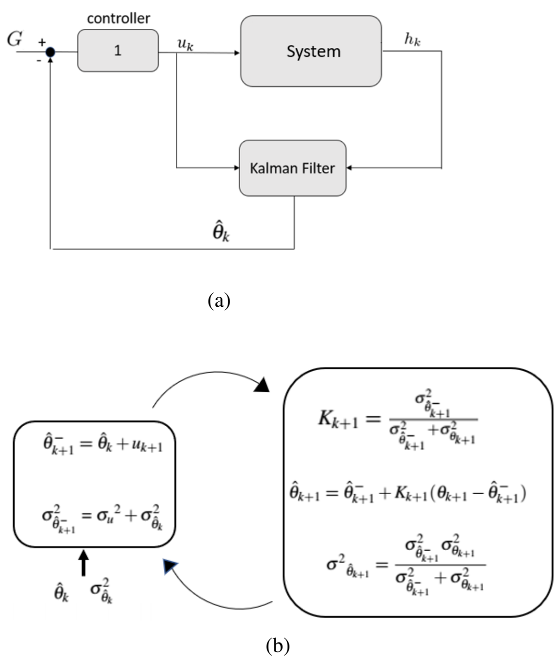


Fig. 3. (a) Block Diagram. G is the goal direction, u_k (input of the system) is the motor command. h_k (output of the system) is the direction of hand motion perceived by the participant *measured* by the sensory system. $\hat{\theta}_k$ is the *estimated* angular direction of hand motion perceived by the participant. (b) Kalman filter equations that we implemented. K_{k+1} is the Kalman gain, $\sigma^2_{\hat{\theta}^-_{k+1}}$ is the variance of the forward model, $\sigma^2_{\theta_{k+1}}$ is the variance of the sensory motor measurement, $\sigma_u{}^2$ is the variance of the motor command. Scheme adapted from [8]

The motor command u_k satisfies $u_k = -(\hat{\theta}_k - G)$, where G is the *goal direction* w.r.t. the mid-line of the plate (e.g. if the participant is instructed to move straight, G = 0°)

Fig. 3b represents the Kalman filter equations using the notation of [8]. The trajectories performed by subjects were simulated setting $w_T = 0.15$. This is in accordance with previous studies that showed a smaller weight of touch compared with proprioception for the estimate of hand displacement [9]. To reproduce the angular direction performed by the participant's hand, we updated the proprioception P as:

$$P_{k+1} = P_k + u_k + \epsilon_{k-1}$$

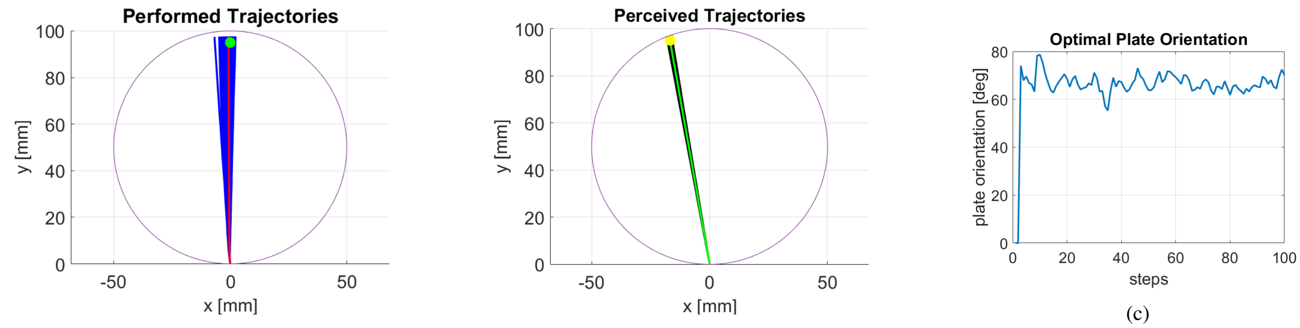
In the equation above, ϵ_{k-1} is the sum of the error term related to motor noise, ϵ_{u_k}, and the one related to the state estimate, $\epsilon_{\hat{\theta}_k}$. The two error terms were sampled from two Gaussian distributions with parameters $N(0, \sigma_u{}^2)$ and $N(0, \sigma_{\hat{\theta}_k}{}^2)$, respectively. The output of the Kalman filter $\hat{\theta}_k$ and the proprioception P_k are used in the next section to design the Model Predictive Control strategy.

III. Optimization problem - Model Predictive Control

The problem to be solved requires finding an optimal ridge plate orientation (T_k) at each time instant k, for guiding an user towards a desired point (defined as *real target*, P_R), while he/she is perceiving to move towards another target (defined *virtual target*, θ_V). To this end, we implemented a cost function $J(k)$ that minimizes both the error between $\hat{\theta}_k$ and θ_V, and the error between P_k and P_R. The cost function is simply defined as follows:

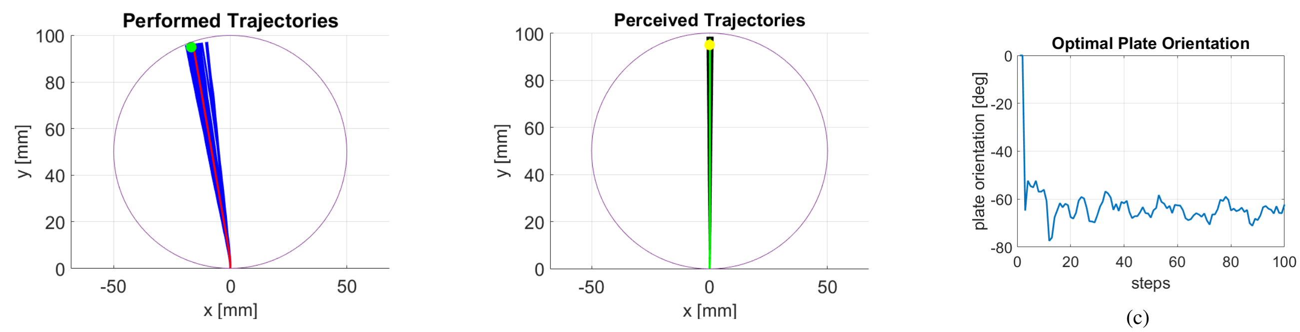
$$J(k) = (\hat{\theta}_k - \theta_V)^2 + (P_k - P_R)^2, \qquad (1)$$

where $\hat{\theta}_k$ is function of the ridge orientation T_k (as presented in the Section II-A). The choice of such a cost function is based on the idea that the hand position has to be guided towards P_R (the angular position of the real object w.r.t. the mid-line of the plate), while the user is perceiving to move towards θ_V (the angular position of the virtual object w.r.t. the mid-line of the plate). The optimal plate orientation T_k is then extracted through a Model Predictive Control strategy, by minimizing the cost function (1) over a time window of 3 steps (i.e., $[k, k+1, k+2]$). The time window length was determined considering the minimum step number for which the performance of our algorithm did not improve if we increased the time window length. Moreover, the optimal plate orientation was constrained between $(-90°, 90°)$ w.r.t. the direction of the virtual target. The motivation behind this is twofold: first of all, if the ridge orientation is exactly ±90° (in modulus) the illusion could not appear, since the participant would simply follow the vertical lines. Secondly, if the rotation is greater that 90° in modulus (e.g., having a rotation α = 120°), it is equivalent of having a rotation of the amount exceeding 90° in the opposite rotational direction (in the example,α = 120° is equivalent to α = -30°). Finally, the initial value of the ridge plate orientation was set to 0° for each simulated condition.



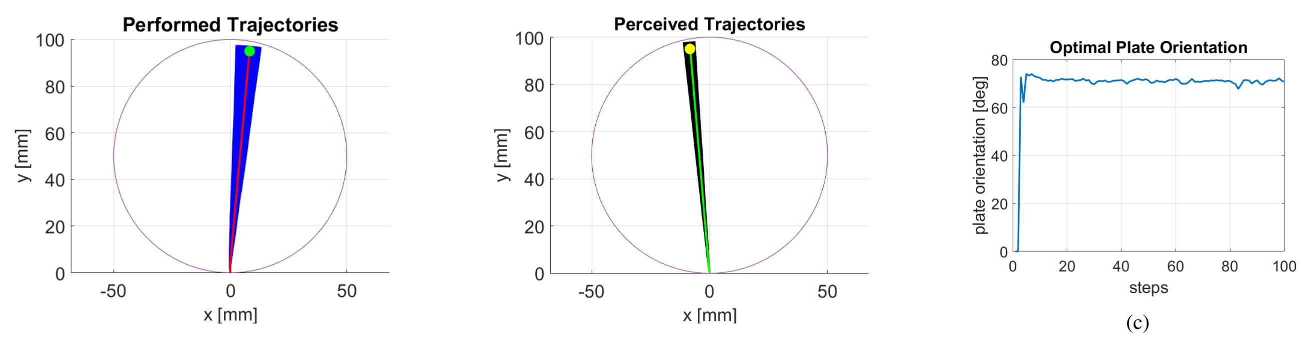
(a) (b) (c)

Fig. 4. **a**: In blue, simulated trajectories performed by a participant and in red the median trajectory. The real target (P_R, green point) is positioned at $0°$ with respect to the mid-line of the plate. **b**: In black, simulated trajectories perceived by a participant and in green the median trajectory. The virtual target (θ_V, yellow ball) is positioned at $10°$ with respect to the mid-line. **c**: The optimal plate orientation for a simulated trial. The starting position of the plate orientation was set to $0°$. The used values for ${\sigma_u}^2$ and w_T are the ones of the *condition 1* Table I



(a) (b) (c)

Fig. 5. **a**: In blue, simulated trajectories performed by a participant and in red the median trajectory. The real target (P_R, green point) is positioned at $10°$ with respect to the mid-line of the plate. **b**: In black, simulated trajectories perceived by a participant and in green the median trajectory. The virtual target (θ_V, yellow ball) is positioned at $0°$ with respect to the mid-line. **c**: The optimal plate orientation for a single simulated trial. The starting position of the plate orientation was set to $0°$. The used values for ${\sigma_u}^2$ and w_T are the ones of the *condition 2* Table I

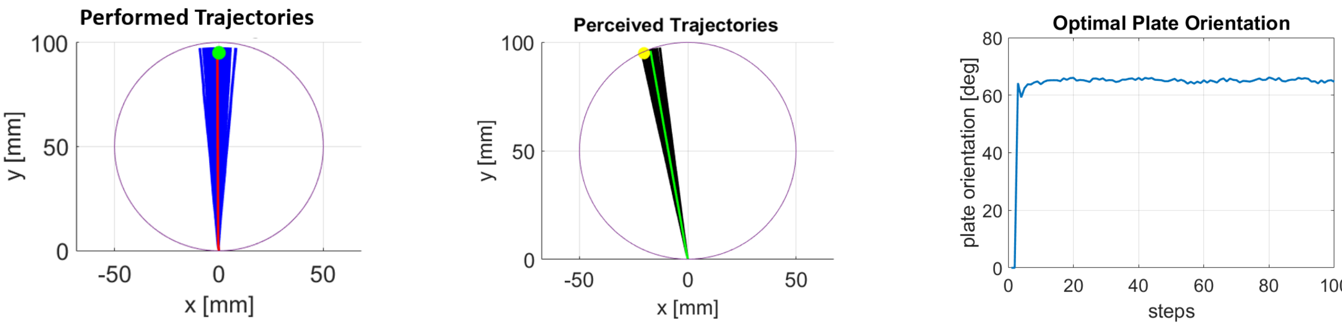


(a) (b) (c)

Fig. 6. **a**: In blue, simulated trajectories performed by a participant and in red the median trajectory. The real target (P_R, green point) is positioned at $-5°$ with respect to the mid-line of the plate. **b**: In black, simulated trajectories perceived by a participant and in green the median trajectory. The virtual target (θ_V, yellow point) is positioned at $5°$ with respect to the mid-line. **c**: The optimal plate orientation for a simulated trial. The starting position of the plate orientation was set to $0°$. The used values for ${\sigma_u}^2$ and w_T are the ones of the *condition 4* Table I

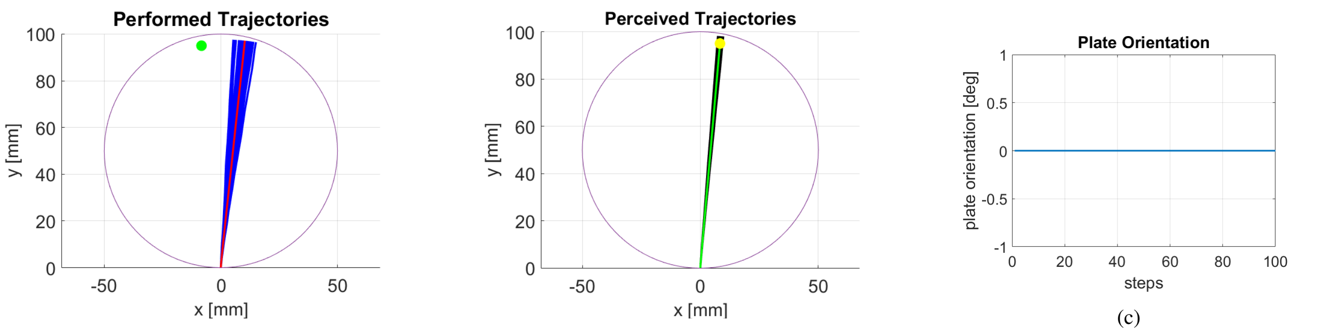
A. Simulations

We simulated 50 participants' trajectories for four different conditions, which consider different values of the weight of the tactile feedback (w_T) and the noise associated to the motor command (please note that when we refer to the motor command noise, we assume a value randomly sampled from a Gaussian distribution with parameter N($0,{\sigma_u}^2$), but for simplicity from here on we refer to motor command noise using only the value of ${\sigma_u}^2$). Particularly, for the four conditions, we assume that the values of w_T change between 0.1 and 0.15, and that ${\sigma_u}^2$ is in a range between 0.5 and 1, in accordance with [2]. For each condition, we decided to simulate six different couples of values for both P_R and θ_V (see Table I), for a total of 24 simulated conditions. The different six couples of P_R and θ_V were chosen so that they always formed the same angular amplitude width - i.e., $10°$. This amplitude was chosen because is the one that gives an higher percentage of trajectories in a rage of $\pm 1.5°$. Of



(a) (b) (c)

Fig. 7. **a**: In blue, simulated trajectories performed by a participant and in red the median trajectory. The real target (P_R, green point) is positioned at $0°$ with respect to the mid-line of the plate. **b**: In black, simulated trajectories perceived by a participant and in green the median trajectory. The virtual target (θ_V, yellow point) is positioned at $12°$ with respect to the mid-line. **c**: The optimal plate orientation for a simulated trial. The starting position of the plate orientation was set to $0°$. The value used for ${\sigma_u}^2$ was 2 and for w_T 0.15. The performed trajectories were for the 60 % of the cases in a range of $\pm 5°$ w.r.t. the position of the real target.



(a) (b) (c)

Fig. 8. **a**: In blue, simulated trajectories performed by a participant and in red the median trajectory. The real target (P_R, green point) is positioned at $5°$ with respect to the mid-line of the plate. **b**: In black, simulated trajectories perceived by a participant and in green the median trajectory. The virtual target (θ_V, yellow point) is positioned at $-5°$ with respect to the mid-line. **c**: The plate orientation was set to $0°$ for the entire trail duration. The used values for ${\sigma_u}^2$ and w_T are 0.1 and 0.15, respectively

course, also values like $P_R = -2°$ and $\theta_V = 8°$ could be taken into consideration. We will see in the Section B that an higher angular value between θ_V and θ_R reduces the performance of our algorithm.

Moreover, for each couple of the two targets, we computed ϕ that is the percentage of the final points of the fifty simulated trajectories that were in a range of $\pm 1.5°$ w.r.t. the *real target*, P_R (see Table I). The range of $\pm 1.5°$ was chosen because a sphere with a diameter smaller than the fingertip diameter reported in [10] could be placed in that range.

B. Results

The results reported in Table I show, for each couple of P_R and θ_V, the percentages of trajectories for which the final point is in a range of $\pm 1.5°$ w.r.t. the real target direction. Then, Fig. 4, 5, 6 report some performed trajecotries, perceived trajectories and the optimal ridge orientation value. Considering all the cases of the *condition 1* (${\sigma_u}^2$ = 0.5, w_T = 0.15), the average percentage of the simulated trajectory final points, which are in a range of $\pm 1.5°$ w.r.t. the real target direction, is 93 $\pm$ 3.3 % (mean $\pm$ std). Then, maintaining the noise of the motor command to 0.5 (${\sigma_u}^2$ = 0.5) and changing the tactile weight to 0.1 (w_T = 0.1) (*condition 2* Table I), the average percentage is 82.7$\pm$ 3 %. Furthermore, increasing the motor command noise (${\sigma_u}^2$ = 1) and setting the tactile weight equal to 0.15 (w_T = 0.15) (*condition 3* Table I) and than to 0.1 (w_T = 0.1) (*condition 4* Table I), the average percentages are 81.3$\pm$3 and 77.8 $\pm$3.5 %, respectively. Moreover, we also tried to increase the value of w_T remaining under the value of 0.5 (the tactile weight must be less than the proprioceptive weight [11]), but the performances did not increase or decrease w.r.t. the aforementioned tested conditions. Then, we decided to test the performace of our algorithm setting the tactile cue weight to 0.05. The results show that the performances get worse w.r.t. the aforementioned cases, with an average percentage of the final points of the performed trajectories that are in a range of $\pm 1.5°$ equal to 40 $\pm$ 5 %. This condition is coherent with [2], where we simulated a tactile impairment during the task execution. In fact, as reported in [3], in case of tactile impairment the tactile channel is noisier and the participants are less influenced by the contribution of tactile feedback during the sliding of the index finger on the ridged plate. Moreover, also for the case of an higher value of the motor command noise ($\sigma_u = 2$), and an higher angular distance between θ_R and θ_V ($\theta_R = 0°$ and $\theta_V = 12°$) the performances got worst with an average percentage of the final points of the performed trajectories that are in a range of $\pm 1.5°$ equal to 60 % (Fig. 7).

Finally, we also tried our algorithm without the MPC control and leaving the plate set to the initial plate orientation (0°) and the perceived trajectories were in the direction of θ_V, but the performed trajectories did not correct towards P_R (Fig. 8).

IV. Discussions

In this paper, we presented the simulation outcomes of an optimization control problem, as a first step towards haptic retargeting applications. Relying on the tactile illusion presented in [2], here we implemented a MPC strategy that computes at each time instant the optimal ridge orientation that would guide, in a virtual environment, the user's hand trajectories towards a real target, while the participant is instructed to move towards a virtual one.

Here, we tried our algorithm considering six different positions of the *real target* and the *virtual target* and changing for these six cases the motor command and the tactile cue noise.

The results showed that the performance of our algorithm is very promising with an average percentage, computed considering all the twelve cases reported in Table I, of the simulated hand trajectory final points in a range of $\pm 1.5°$ w.r.t. the angular position of the desired final goal of $\sim 80\%$.

Moreover, to test the robustness of our algorithm we performed simulations with the six couples of P_R and θ_V reported in Table I setting the tactile noise as in [2] to simulate a tactile impairment. As expected, in this case, the performance of the algorithm got worst since in the case of tactile impairment humans rely less on the motion estimate given by tactile feedback. Finally, it is important to stress the fact that user tests are necessary to validate the algorithm and find possible errors and limitations.

V. Conclusions and Future Work

In this work, we presented a promising method to implement haptic retargeting using texture-induced illusions. Indeed, implementing this technique using touch and not vision implies low cognitive load. In fact, touch and proprioception are seamlessly integrated, i.e. they are both parts of the same system (the somatosensory system). In future work, we will try our algorithm with real participants. We are aware that this will not be straightforward since different important aspects should be considered. For example, we should consider that the weight of tactile feedback (w_T) and the variance of the motor command (${\sigma_u}^2$) are parameters that vary from participant to participant. Thus, a strategy to estimate these parameters for each participant is necessary. A possible way could be performing a calibration before the execution of the experiment. During the calibration experiment, the participants should slide the finger straight ahead on a plate with the ridges pre-oriented at a certain orientation (experiment reported in [2], [12]). These trajectories should then be compared with the ones obtained from the Kalman filter model explained in Section II-A to extract for each participant her/his optimal value of w_T and ${\sigma_u}^2$.

Furthermore, another difference is that in a real experiment, the proprioception P_k is the angle w.r.t. the mid-line of the plate of the real finger trajectory performed by the participant that should be acquired with a motion capture system. Finally, we will also investigate the possibility of using the here presented technique to increase virtual content accessibility to blind or visually impaired people.

Acknowledgment

This work is supported by the European Union's Horizon 2020 research and innovation program under grant agreement No. 871237 (Sophia) and by the Italian Ministry of Education and Research (MIUR) in the framework of the CrossLab project (Departments of Excellence), and in the framework of PRIN (Programmi di Ricerca Scientifica di Rilevante Interesse Nazionale) 2017 with the project TIGHT, grant number 2017SB48FP

References

[1] M. Azmandian, M. Hancock, H. Benko, E. Ofek, and A. D. Wilson, "Haptic retargeting: Dynamic repurposing of passive haptics for enhanced virtual reality experiences," in *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems*. ACM, 2016, pp. 1968–1979.

[2] A. Moscatelli, M. Bianchi, S. Ciotti, G. Bettelani, C. Parise, F. Lacquaniti, and A. Bicchi, "Touch as an auxiliary proprioceptive cue for movement control," *Science advances*, vol. 5, no. 6, p. eaaw3121, 2019.

[3] G. C. Bettelani, A. Moscatelli, and M. Bianchi, "Towards a technology-based assessment of sensory-motor pathological states through tactile illusions," in *2018 7th IEEE International Conference on Biomedical Robotics and Biomechatronics (Biorob)*. IEEE, 2018, pp. 225–229.

[4] ——, "Contact with sliding over a rotating ridged surface: the turntable illusion," in *2019 IEEE World Haptics Conference (WHC)*. IEEE, 2019, pp. 562–567.

[5] E. J. Gonzalez and S. Follmer, "Investigating the detection of bimanual haptic retargeting in virtual reality," in *25th ACM Symposium on Virtual Reality Software and Technology*, 2019, pp. 1–5.

[6] G. C. Bettelani, S. Fani, P. Salaris, and M. Bianchi, "A model predictive control framework to control hand movements relying on tactile illusions."

[7] A. Bicchi, E. P. Scilingo, E. Ricciardi, and P. Pietrini, "Tactile flow explains haptic counterparts of common visual illusions," *Brain research bulletin*, vol. 75, no. 6, pp. 737–741, 2008.

[8] R. E. Kalman, "A new approach to linear filtering and prediction problems," *Journal of Basic Engineering*, vol. 82, no. 1, pp. 35 – 45, 1960.

[9] A. Moscatelli, M. Bianchi, A. Serio, A. Terekhov, V. Hayward, M. O. Ernst, and A. Bicchi, "The change in fingertip contact area as a novel proprioceptive cue," *Current Biology*, vol. 26, no. 9, pp. 1159–1163, 2016.

[10] E. Battaglia, M. Bianchi, M. L. D'Angelo, M. D'Imperio, F. Cannella, E. P. Scilingo, and A. Bicchi, "A finite element model of tactile flow for softness perception," in *2015 37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, Aug 2015, pp. 2430–2433.

[11] A. Moscatelli, M. Bianchi, A. Serio, A. Bicchi, and M. O. Ernst, "Sensorymotor synergies: Fusion of cutaneous touch and proprioception in the perceived hand kinematics," in *Human and Robot Hands*. Springer International Publishing, 2016, pp. 87–98.

[12] M. Bianchi, A. Moscatelli, S. Ciotti, G. C. Bettelani, F. Fioretti, F. Lacquaniti, and A. Bicchi, "Tactile slip and hand displacement: Bending hand motion with tactile illusions," in *2017 IEEE World Haptics Conference (WHC)*. IEEE, 2017, pp. 96–100.