Material Properties Determine how We Integrate Shape Signals in Active Touch

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Abstract

When sliding a finger across a bumpy surface, the finger follows the surface geometry (position signal). At the same time the finger is exposed to forces related to the slope of the surface (force signal) [1]. For haptic shape perception the brain uses both signals integrating them by weighted averaging [2]. This is consistent with the Maximum-Likelihood-Estimate (MLE) model on signal integration, previously only applied to passive perception. The model further predicts that signal weight is proportional to signal reliability. Here, we tested this prediction for the integration of force and position signals to perceived curvature by manipulating material properties of the curve. Low as compared to high compliance decreased the reliability and so the weight of the sensorily transduced position signal. High as compared to low friction decreased the reliability and so the weight of the transduced force signal. These results extend the MLE-model to situations involving active touch.

1. Introduction

Perception is based on multiple sources of sensory information – we simultaneously and continuously obtain sensory inputs from our eyes, ears, and the skin. Some of the inputs provide information about the same physical property. For instance, we can both see and feel the shape of an object that we hold in our hands. The question of how our brain integrates such redundant signals into a unitary percept has been studied intensively in the recent past.

The Maximum-Likelihood-Estimate (MLE) model has been proven to be a good description for signal integration strategies [3]. According to this model the brain takes into account all signals available for a property, derives estimates (s_i) for the property from each signal (i) and, then, combines all estimates into a coherent percept (P) by weighted averaging:

$$P = \sum_i w_i s_i \text{ with } \sum_i w_i = 1; \quad 0 \le w_i \le 1 \qquad (1)$$

Estimates derived from each signal are prone to noise (σ_i^2). According to the MLE model the system can reduce the noise in the combined percept by averaging different estimates [4]. Noise reduction can be optimized, if the signal weights w_j depend on the reliabilities ($Rj = 1/\sigma_j^2$) of the individual estimates. "Optimal" weights – resulting in the maximal reliability of the final percept (R_P) – are proportional to the relative reliabilities of the signals – given that noise distributions are independent from each other [5]:

$$R_P \le R_i \forall i \text{ with } \max(R_P) \text{ for } w_j = \frac{R_j}{\sum_{i=1..,j,..N} R_i} \forall j \qquad (2)$$

Experiments on within-visual signal integration as well as on crossmodal visuo-haptic and visuo-auditory integration confirm that the human brain integrates sensory information in such an optimal way [6-10]. Not much systematical research, however, has been done on signal integration within active haptic perception. From an informational point of view active touch is substantially different from the passive perceptual situations studied so far. In active touch observers are able to (and do) actively manipulate their informational inflow [e.g., 11]. First systematical studies on signal integration within active touch are, nonetheless quite recent.

Robles-de-la-Torre and Hayward [1] distinguished between well-defined position and force signals to haptically perceived shape: When sliding a finger across a bump on a surface, the finger follows the geometry of the bump (position signal). At the same time the finger is exposed to forces – tangential to the movement – that are related to the slope of the bump (force signal). A custom-made device dissociated position and force signals in the haptic perception of small-scale bumps and holes (3 mm amplitude): Participants in this experiment predominantly reported to feel the class of shapes (bumps or holes) indicated by the force signals. Drewing and Ernst [2] extended this research. They systematically disentangled force and position signals to the perception of curvature and quantified the perceived curvature. The result was that perceived curvature could be well predicted from weighted averaging of the two signals. This is consistent with equation 1 in the MLE model. Further, they found that the weights of force and position signals change with the magnitude of the curvature. This result is consistent with reliability-dependent signal weighting (equation 2). However, compelling evidence that the weights actually shift with the reliability of the signals was missing.

The purpose of the present study was to manipulate the reliabilities of force and position signals for haptic shape in a predictable manner and to test whether signal weights systematically increase with the signal's reliabilities – like predicted by equation 2 in the MLE model. We employed natural causes of reliability change. On the one hand, high surface compliance can be expected to decrease the reliability of the position signal as compared to low compliance. This is because finger pressure influences the position of the finger more when touching a highly as compared to a hardly compliant surface and unavoidable motor variability [cf. 12, 13] in finger pressure should add noise to the sensorily transduced position signal. Then, noise in the position signal stemming from motor variability should be higher for high than for low compliance surfaces. On the other hand, high friction can be expected to decrease the reliability of the force signal as compared to low friction. Friction is a complex physical phenomenon widely depending on the dynamics between the contact surfaces [14] and frictional forces are – like the force signals to shape – tangential to the movement. Variability in the dynamic of the finger movement should cause varying effects of friction which interfere with the sensorily transduced force signal. The more so, the larger the effects of friction.

From the above relations, the principle of reliability-dependent weighting predicts that the weight of the force signal is higher for low as compared to high friction surfaces and the weight of the position signal is higher for low as compared to high compliance surfaces (and – because the signal weights sum up to 1 – vice versa for position and force signal weights, respectively).

In the present experiment, we measured sensorily transduced signal information and signal weights under each combination of high and low surface friction with high and low surface compliance. Using the PHANToM force-feedback device we constructed haptic curve stimuli, in which force and position signals to curvature were not consistent (using curvatures [= 1/radius] of 14 and 24 m^{-1}). Using the method of double-staircase, we determined the point of subjective equality (PSE) between the curvature of these curves and 'natural' curves (i.e., with consistent position and force signals). From the PSE data and the curvatures indicated by either signal we determined the signal weights (for details see [2]).

2. Experiment

2.1. Methods

2.1.1. Participants. 18 right-handed observers (equal numbers of females and males) without any sensory or motor impairments of their right index finger participated for pay. All were naïve to the purpose of the experiment.

2.1.2. Apparatus. Participants sat in front of a custom-made visuo-haptic workbench (Fig. 1A) comprising a PHANToM 1.5A haptic force feedback device and a 21"-computer screen. The participant's right index finger was connected to the PHANToM via a thimble-like holder, which allows for free finger movements having all six degrees of freedom in a 20 cm^3 workspace. Simultaneuosly, the participants looked – fixated by a chin rest – via a mirror onto the screen (52-cm viewing distance).

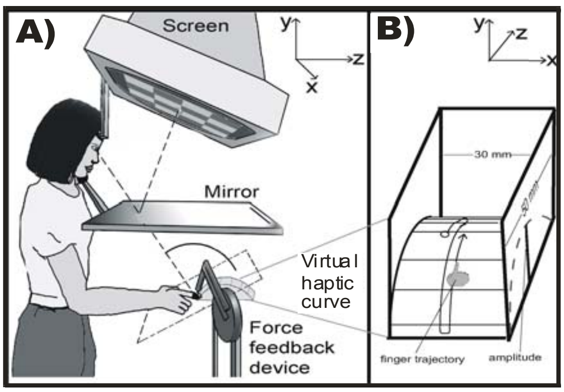

Figure 1. A) Visuo-haptic workbench, B) Haptic curve and movement trajectory

The mirror enables spatial alignment of visual with haptic display. In the present experiment, however, visual display was used only to guide participants through the experiment. A custom-made software running on a PC controlled devices and experiment, collected responses and recorded the movement of the finger (100 Hz).

2.1.3. Stimuli. Haptic stimuli were generated by using the PHANToM force-feedback device that simulates 3D-objects by applying appropriate reaction forces F_S depending on three-dimensional finger position P within its workspace. When touching a virtual object, reaction forces are given in direction normal to the object's surface. Force magnitude increases with the finger's indentation of the surface following a spring model:

$$\left|\vec{F}_S\right| = D \cdot i_S\,, \quad \frac{\vec{F}_S}{\left|\vec{F}_S\right|} = \vec{n}_p \tag{3}$$

D denotes the spring coefficient and i the indentation depth. When stroking across the surface, the PHANToM can apply frictional forces F_F counteracting the movement:

$$\left|\vec{F}_F\right| = f \cdot \left|\vec{F}_S\right| \tag{4}$$

f denotes the friction coefficient. In the real world f is usually different for static and dynamic situations (finger does not move vs it does). We implemented just dynamic friction in that f depended on the finger's velocity v:

$$f = \begin{cases} 0 & \left|\vec{v}\right| < DV \\ \dfrac{\left(\left|\vec{v}\right| - DV\right)}{v_{Sat} - DV} f_{Sat} \quad \text{for} & DV \le \left|\vec{v}\right| \le v_{Sat} \\ f_{Sat} & \textit{otherwise} \end{cases} \tag{5}$$

DV equalled 20 mm/s and v_{Sat} 12 cm/s. Virtual objects that are constructed according to these equations provide an explorer with consistent position and force signals to the object's geometry.

Here, we constructed curves (sections of a circle) where onset position and magnitude of reaction forces indicated one curvature (position signals), but the directions of the reaction forces were taken as the normals of another curvature (force signals, Fig. 2). Starting at the curves apexes we projected force directions on geometry one-to-one in terms of curved distance of a point from the apex. The curves arched in the horizontal plane along the observer's depth axis. They were touched from above and finger movement was restricted by vertical haptic walls to be within an area of 30 mm width x 50 mm depth and by another horizontal wall to be no more than 25 mm above the curve's amplitude (see Fig. 1B).

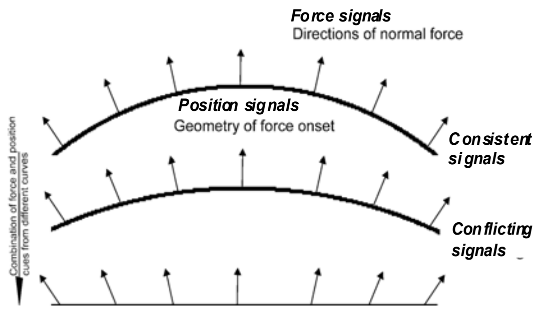

Figure 2. In the upper shape the directions (arrows) of reaction forces (=force signal) are normal to the surface geometry (=position signal) – like in 'natural curves'. In the below shapes force directions from the upper shape are combined with shallower (force onset) geometries: The position signal indicates a less curved shape than the force signal

2.1.4. Design and Procedure. The experimental design comprised four within-participant variables: Compliance (high vs low), Friction (high vs low), Force signal curvature (14, & 24 m^{-1}), and Position signal curvature (14, & 24 m^{-1}). Compliance and Friction were varied by manipulating the spring coefficient D in equation 3 (0.2 vs 0.6 mm/N) and the friction coefficient f_{Sat} in equation 5, respectively (0.6 vs. 0.2). Under each of the four combinations of material properties, we used four (convex) standard curves completely combining position and force signals related to curvatures of 14, and 24 m^{-1}. We measured the points of subjectively equal curvature (PSE) of these standard curves compared to comparison curves having the same surface material properties, but consistent force and position signals – using one double-staircase per standard.

Each single trial in each staircase consisted of the sequential presentation of a standard and a comparison curve (order randomized). Participants self-initiated the curves' presentations and, then, starting at the curve's apex made one complete stroke across each curve (forth – back – forth; Fig. 1B). After the second curve participants decided by a button press which of the two curves had felt more convex; during the curve presentation the screen went black.

In each double-staircase, trials of two adaptive staircases (1-up/ 1-down) were interleaved. The up-staircase (down-staircase, respectively) started with a comparison curve the curvature of which was obtained by adding (subtracting) 14 m^{-1} to (from) the higher (lower) curvature value of the two values related to the two standard's signals. In succeeding trials of both staircases, the curvature of the comparison curve was reduced by a certain step, if the participant in the previous trial of that staircase had indicated the comparison to be more convex than the standard and vice versa. Initial step sizes were 8 m^{-1}, with each reversal of step direction (and response) it was halved - down to a smallest step size of 2 m^{-1}. A staircase stopped after 8 non-reducing reversals. The average of the comparisons' curvatures across these 8 reversal points estimated the PSE (cf. Falmagne, 1986).

The order of double-staircases was random; the experiment lasted about 3 hours including 4 breaks, instructions and initial practice.

2.1.5. Data Analysis. The first part of the data analysis dealt with our expectations of noise in the sensorily transduced position and force signals. Unsystematic deviations of actual finger amplitudes from a perfectly curved trajectory indicate noise in the transduced position signal. Angular deviations of actual force direction from force directions related to a perfect curve indicate noise in the transduced force signal (Fig. 3). For each standard stimulus we regressed the actual finger amplitudes during the stroke on the finger position along the shape's base and the actual force directions on the finger position along the shape's surface path – using the appropriate functions that already defined the force and position signals. The standard error of the residuals, then, provided us with a measure of noise in the sensorily transduced position and force signals, respectively[1]. Individual averages of these values entered two ANOVAs with the two within-participant variables Compliance and Friction.

In the second part of the data analysis we focused on the participants' percept. Individual PSEs entered into an ANOVA with all four within-participant variables. Further, from the individual PSEs of standard curves with inconsistent force and position signals (C_{force} & $C_{position}$) we calculated individual force signal weights (w_{force}, note that $w_{position}$ equals $1\text{-}w_{force}$).

$$w_{force} = \frac{PSE - C_{position}}{C_{force} - C_{position}} \qquad (6)$$

Averaged individual force signal weights for each surface material entered an ANOVA with the two within-participant variables Compliance and Friction.

[1] We also checked for systematic bias in transduced signals. Observed bias, however, did not change the main results and, hence, is not further reported.

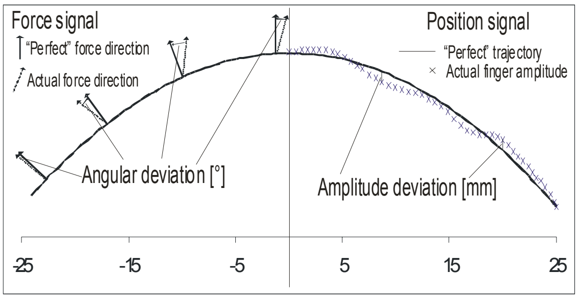

Figure 3. Indicators of noise in sensorily transduced force and position signal

2.2. Results and Discussion

2.2.1. Sensorily transduced information. Noise in the sensorily transduced information is plotted in Figure 4 A and B for the force and position signal, respectively. A two-way ANOVA on noise in the position signal revealed a significant effect of Compliance, $F(1, 17)=282.9$, $p<.001$. As expected the transduced positional information was considerably more noisy, when the observers followed the geometry of a highly compliant surface as compared to a low compliance surface. Noise increased by about 100 %. The effect of Compliance was exclusive, Friction did not have any reliable effect on positional noise.

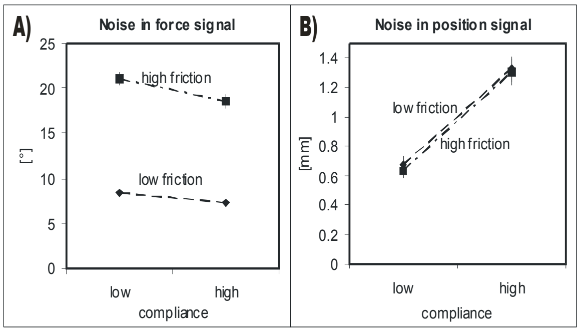

Figure 4. Average noise in sensorily transduced force and position signals and standard error as a function of material property

In contrast, a two-way ANOVA on noise in the force signal revealed a significant effect of Friction, $F(1, 17)=641.2$, $p<.001$. Also as expected the transduced force information was considerably more noisy (about 150 %) under high as compared to low friction. We also found effects of Compliance on force signal noise (main effect: $F(1, 17)=36.5$, $p<.001$, interaction: $F(1, 17)=14.5$, $p<.001$). These, however, tended to be small (noise increase of only 14% from low to high compliance).

Taken together, noise in the transduced force signal mainly covaried with the surface's friction and noise in the transduced position signal exclusively covaried with the surface's compliance. These results confirm our expectations on the effects of the surface material on sensory transduction. Further, it is highly reasonable to assume that the reliability of a certain signal directly depends on the measurable noise of this signal in sensory transduction [cf. 6]. Thus, our results on signal noise provide good evidence that low as compared to high compliance selectively decreased the reliability of the position signal and high as compared to low friction decreased the reliability of the force signal.

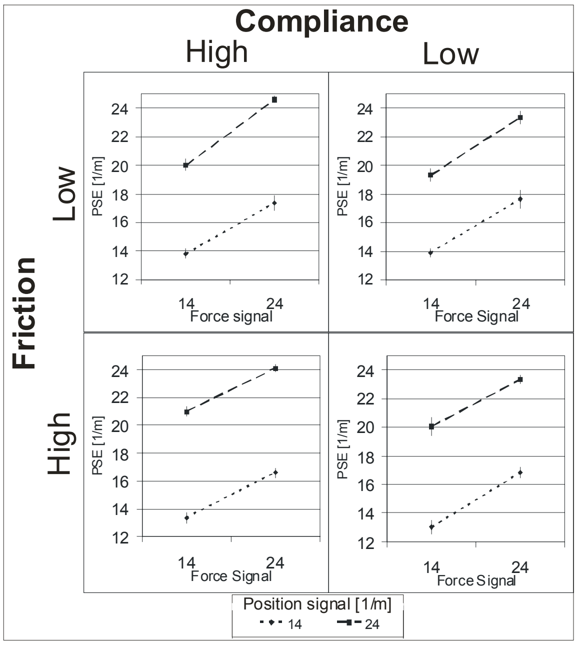

Figure 5. Average PSEs and standard error

2.2.1. Percept. Individual PSEs (Fig. 5) entered a four-way ANOVA with the within-participant variables Force signal, Position signal, Friction and Compliance. Main effects of Force Signal, F(1, 17)=153.9, p<.001, and Position Signal, F(1, 17)=785.9, p<.001, indicated that both force and position signals contributed to the participants final percept of curvature. This result confirms previous work [2]. Further, interactions of Position signal with Compliance, F(1, 17)=14.2, p<.01, and Friction, F(1, 17)=5.8, p<.05 indicated that the contribution of the signals was modified by the surface material.

A two-way ANOVA of the force signal weights with the within-participant variables Compliance and Friction (Fig. 6) clarifies how signal contribution depended on surface material: The force signal weight was higher under low as compared to high friction, *F*(1, 17)=7.3, *p*<.02, and it was higher under high as compared to low compliance, *F*(1, 17)=13.0, *p*<.01. There was no reliable interaction.

These results match with our hypothesis that high friction lowers the contribution of force signals to perceived shape and high compliance lowers the contribution of position signals. Moreover, the first part of the analysis supported the assumption that high friction lowers the reliability of the force signal and high compliance lowers the reliability of the position signal. Taking the two parts of data analysis together, we found good evidence that the weights in the integration of force and position signals to haptic shape systematically depend on the signals' reliabilities. That is, our results support the MLE model's prediction of reliability-dependent weighting in human signal integration (equation 2) for the case of haptically perceived shape.

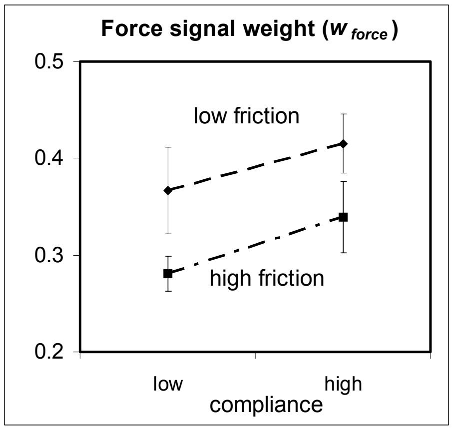

Figure 6. Average force signal weights (w_{force}) and standard error (note that $w_{position} = 1\text{-}w_{force}$)

3. Conclusion

We have good evidence that the brain acts as if it reassigns the weights of haptic force and positional signals to perceived shape when the reliability of the signals changes. A similar argument has been made in other domains, i.e. for within-visual, visuo-haptic or visuo-auditory combination of different signals. These reports, however, used passive stimulation and mostly artificial manipulations of sensory reliability. We employed natural causes of variation in signals: differences in surface material. This correlation is ubiquitous in everyday perception. Hence, observers in our study were likely to use commonplace rather than ad hoc strategies [15]. Most importantly, signal reliability in our stimuli depended on the interaction of an active observer with the stimulus, and, partially, was conditional on noise stemming from motor control. The fact that also in active touch weight shifts correspond to an observer accounting for reliability shifts suggests that this principle is pervasive.

In conclusion, we demonstrated that signal integration in active haptic perception obeys both principles formulated in the MLE model. However, there are also hints that individual movement variations can modulate integration [16]. It is an interesting question for future research, to determine how movement control influences signal integration and whether movement variations may be strategically exploited to optimize the input for signal integration in active perception [12].

4. References

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