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Haptic Search for Movable Parts

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How do we know that we are touching 1 single object instead of 2 different ones? An important cue is movability: When different sources of input can move independently, it is likely that they belong to different objects or that the object consists of movable parts. We hypothesize that the haptic feature "movability" is used for making this differentiation and we expect movability to be detected efficiently. We investigated this hypothesis by using a haptic search task. In Experiment 1, participants were asked to press down on piano-like keys and respond whether 1 key was movable while the rest were static or the other way around (*detection only*). Search strategy was determined by comparing performance of 4 response time models. This showed that the search slope for the target absent and present trials was the same (detection without localization model). In Experiment 2, we asked participants to *localize* the target, in order to investigate whether localization is an extra processing step. In this case our localization after detection model described the data best. This suggests that the target was detected independent of localization. To our knowledge this is the first time such a search strategy has been reported in haptic search, and it highlights the special role of the detection of movability.

Public Significance Statement

Have you ever dropped an object because you forgot you were holding 2 instead of 1? It is important to know that we are holding multiple objects: We can use the haptic movability cue to tell how many objects we are holding. Because it is such an important source of information, we expect movability to be detected fast. We investigated this hypothesis in a haptic search task and indeed found that movability is detected efficiently and without localization. We found that the target is first detected, and that localization is performed in a second processing step. This pattern of response times has not been found for other haptic features. Our findings highlight the importance of movability as a cue in haptic perception.

Keywords: haptic search, movability, response time models

In order to recognize objects haptically, we need to decide which parts belong together and which do not. If the things we are touching can move with respect to each other, we are either holding two separate objects or one object that consists of multiple parts, such as a pair of pliers or a set of keys. This is a rather complex puzzle that our brain seems to solve effortlessly in daily life.

We can decide whether parts are belonging together by taking into account whether the materials of the parts are similar, whether they form a continuous shape, or whether they are close to each other or far apart. Perceptual grouping has indeed been shown in the haptic modality for these types of object characteristics (Chang, Nesbitt, & Wilkins, 2007; Frings & Spence, 2013; Overvliet, Krampe, & Wagemans, 2012; Prieto, Mayas, & Ballesteros, 2014), indicating that our brain organizes incoming haptic information by what most likely belongs to one object. For example, two rough patches are more likely to belong to one object as compared to a rough and a smooth patch (Van Aarsen & Overvliet, 2016). However, if we touch two parts that are similar in material but can move independently with respect to each other it is highly unlikely we are holding a single object. Relative movability of objects and object parts is a typical *haptic* property[1], and it is important to detect quickly, for example when we are holding two objects, but erroneously assume it is one, we may drop an object. This detection mechanism of whether we are holding one or multiple objects has been shown to be fast and accurate (Plaisier, Bergmann Tiest, & Kappers, 2009a). This suggests that the cue that is used to solve this task can be detected efficiently.

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[1] We distinguish here between movability, which is perceived by actively manipulating objects, and movement, which can also be perceived through vision.

Here, we hypothesize that the detection of relative movability plays a critical role in deciding whether we are touching one or multiple objects and thus that relative movability should be detected efficiently. We tested this hypothesis by investigating search efficiency for haptic relative movability. Up to now, research into haptic search efficiency (or feature saliency) has mainly focused on tactile properties such as raised line patterns or material properties (Lederman, Browse, & Klatzky, 1988; Lederman & Klatzky, 1997; Overvliet, Mayer, Smeets, & Brenner, 2008; Overvliet, Smeets, & Brenner, 2008, 2010; Plaisier, Bergmann Tiest, & Kappers, 2008, 2009b; Van Polanen, Bergmann Tiest, & Kappers, 2012b), and there have been only few studies involving movability in touch in general. It has been shown that the detection of a static ball among a field of balls that could rotate is efficient (Van Polanen, Bergmann Tiest, & Kappers, 2012a). Moreover, haptic figure-ground segregation seems to be easier when the figure was moveable as opposed to being fixed in place (Pawluk, Kitada, Abramowicz, Hamilton, & Lederman, 2010, 2011).

In the current study, we investigated search efficiency for movability. We asked participants to search for either a movable target between static distractors or a static target between movable distractors, presented to the finger pads of one hand. In the first experiment participants only had to detect a target, whereas in a second experiment they also needed to localize it. We did this because *detecting* movability and *localizing* movability may be separate processes. As Sternberg already mentioned in 1969, RTs to stimuli are defined by multiple stages of processing (Sternberg, 1969). In visual search the separation between localization and detection has always been a point of discussion. On the one hand, the *feature integration theory of attention* (Treisman & Gelade, 1980) has claimed that localization is a separate step from detection. However, other studies have claimed the opposite and say that detection and localization can be done in parallel or are actually the same process (Green, 1992; Sagi & Julesz, 1985). In haptics, as far as we know, only one study has looked into this issue. Purdy, Lederman, and Klatzky (2004) asked participants to either detect or locate a target between distractors, on the basis of roughness, edge, relative position. and relative orientation. The search slopes did not reveal any differences between localization and detection. However, the intercept showed a cost for localization. The cost for localization was larger for spatial characteristics as compared to texture and edge; this gives additional support to earlier findings that search for roughness and edge are among the most efficient (Lederman & Klatzky, 1997; Overvliet, Smeets, & Brenner, 2007).

In the current study, we compared the performance of different response time models to determine the search strategy that was used and whether this was a multiple stage process with detection and localization as distinct steps. As mentioned above, we hypothesize that movability is processed efficiently, resulting in a parallel search pattern. Moreover, we predict no additional costs for localization.

We fitted several response time models and compared the goodness of fit of these models. First, we fitted serial and parallel search models as introduced by Overvliet et al. (2007). These models assume that serial and parallel haptic search do not only differ in the increase in the time required to find the target when more items are present. They also contain different relationships between the RTs in the target present and target absent conditions, with target absent conditions associated with longer search times as compared to target present conditions, given a certain amount of items in the display. However, visual inspection of the data suggested that the parallel and serial response times were similar for all numbers of items. This behavior is not predicted by either the serial or the parallel model. Both models assume that localization of the target happens *before or simultaneously with* detection. However, an alternative explanation would be that the target is detected without localization. In other words, participants would in that case not need to examine the individual fingers at all in order to detect the target, but would still know about the presence of the target. This would lead to even more efficient search than that described by the parallel search model.

Therefore, we decided to fit two more models, which assume localization to be independent of detection (*detection without localization model*), and one in which we assume target present trials to have larger slopes than target absent trials (*localization after detection model*). Both of these models consist of linear functions defined by a response-times slope and an intercept. The detection without localization model assumes that target present and absent trials have the same slope. This is opposite to the serial and parallel search models in which the search functions differ by definition, with target absent exploration times higher as compared to target present slopes. It is assumed that in target absent trials participants have to explore all the items in the display before deciding the target is absent, whereas in target present this decision can be made directly upon target encounter (which is—in serial search—on average after exploring half of the items in the display). However, if the presence or absence of a target can be detected without the need to localize it first, there is no reason for target absent and present slopes to differ. The *localization after detection model* assumes that localization is performed after detection: This results in different response time slopes with *target present* being larger than *target absent*. This model assumes that first a decision is made on the presence of a target, and subsequently—if present—the target is localized by examination of all fingers or items. This means that there is an additional cost for localizing the target, resulting in a larger slope for target present trials. When the target is absent no localization needs to take place.

Our results from Experiment 1 show high search efficiency for relative movability. The detection without localization model performed best indicating equal target present and absent slopes and that search was performed efficiently without the need to localize the target. Furthermore, we find that search slopes for movable target and static targets did not differ, indicating equal search efficiency (i.e., no search asymmetry). This contrasts with other haptic search studies in which a search asymmetry is often found (Lederman & Klatzky, 1997; Overvliet, Mayer, et al., 2008; Overvliet et al., 2007; Plaisier et al., 2008, 2009b; Van Polanen et al., 2012a). In Experiment 2 we found that the localization after detection model performed best. This shows that, unlike other haptic characteristics, detection of movability precedes localization.

Experiment 1

Method

Participants. Twelve participants took part in this experiment (mean age 21.9 ± 1.4 years, 11 right-handed according to the Edinburgh Handedness Inventory (Oldfield, 1971). All were naive to the purpose of the experiment. The study was carried out in agreement with the ethical principles regarding research with human participants as specified in The Code of Ethics of the World Medical Association (Declaration of Helsinki). The study was part of a program approved by the ethical committee of the Faculty of Human Movement Sciences at VU University. The participants gave written informed consent prior to participation.

Stimuli & apparatus. The stimuli were presented using a custom-built device that had four keys similar to that of a piano (see Figure 1). Only one finger could be placed per key (key width 2 cm). The keys moved downward when pressed and springs underneath made the keys move upward upon release. The spring constant of the springs was 1.3×10^2 N/m so the keys could be pressed down easily. Contrary to a piano key, the keys did not tilt when pressed. Instead, they moved straight up and down. All four keys could be pressed down independently. The maximum displacement of a key was 4 cm. Each key could also be mechanically jammed to prevent it from moving. When jammed, the displacement of a key was less than a millimeter. The surface of the keys was made out of smooth metal. Each key was considered an item. The whole device was placed on a computer interfaced precision scale (Mettler Toledo SPI A6). As soon as the participant touched the stimulus the weight change triggered the onset of the response time measurement. The height of the scale remained stable when pressed. The scale had a time delay of 90 ms, as measured by (Van Polanen et al., 2012a), and this delay was added to the raw data. Response time measurement was terminated by a vocal response that was registered with a microphone. The threshold to trigger the voice key was set for each participant individually prior to the start of the experiment by asking participants to repeatedly say "yes" and "no." This enabled us to set the threshold higher for participants with a naturally loud voice and to reduce the chance of having external sounds in the environment trigger the voice key. The threshold was further adjusted during the practice trials if needed. In the sporadic case that a participant triggered the voice key unintentionally (e.g., by sneezing) or when there was a loud sound in the environment, we repeated the trial at the end of the experiment (less than 5% of the trials).

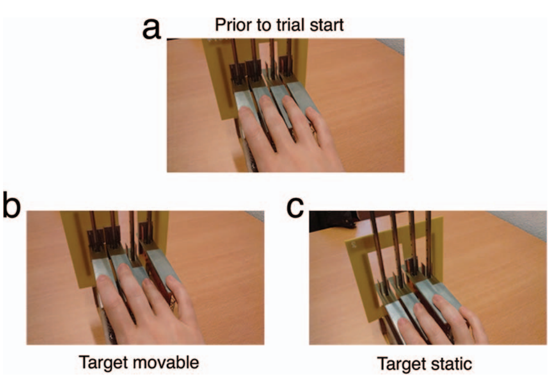

Figure 1. The set-up. (a) Prior to the start of the trial the fingers hovered above the keys and the keys were level at this point. This is an example of a four items trial in which the participant was instructed to use four fingers. (b) Participants started the trial by pressing all fingers down simultaneously. In this example the target was movable among static distractor. (c) Example of a trial in which the target was static and the distractors were movable. See the online article for the color version of this figure.

In Experiment 1 there were two experimental conditions: target movable, distractors static; and target static, distractors movable. In the target movable condition all keys were jammed except for the target and vice versa in the target static condition. In half of the trials a target was present. Participants performed both conditions in counterbalanced order. There could be 2, 3, or 4 items, which were presented in trial blocks. The number of items was varied by instructing the participants to use only the index and middle finger (2 items), index, middle, and ring finger (3 items), or all fingers except for the thumb (4 items). This method of varying the number of items has been used previously (Overvliet, Mayer, et al., 2008; Overvliet et al., 2007). Each number of items was presented 40 times, 20 times target present and 20 times target absent. Each number of items was presented in two separate blocks of trials. The order of blocks was counterbalanced within participants, following an ABCCBA design, and also counterbalanced across participants (e.g., BACCAB or ACBBCA). The likelihood that a target item was presented to a certain finger was equal (or close to equal for the 3 fingers condition) across the fingers. The order of the two conditions (target movable and target static) was counterbalanced over the participants.

Procedure. A screen with a curtain was placed between the participant and the set-up so participants could not see the setup or their hand. The participants hovered their fingers above the keys of the set-up and were instructed to start a trial by simultaneously pressing down with the instructed number of fingers and to respond whether a target item was present by saying "yes" or "no." They were told to do this as fast as possible, but also to be correct. Participants received feedback from the experimenter on whether the answer was correct after every trial. Incorrectly answered trials were repeated at the end of a trial block. Prior to the start of an experiment the participants performed 18 practice trials (6 for each number of fingers) to become familiar with the task.

Control experiment. To test whether response times systematically varied with the finger under which the target was presented, a control experiment was carried out. In this experiment participants ($N = 9$, none had participated in the main experiments) had to respond whether a static target was present while the location of the target was varied and the number of items was always four. In half of the trials the target was absent. Ten trials per target location were performed plus 40 target absent trials (80 trials total). A repeated measures ANOVA on the response times with finger as within-participants factor showed no significant main effect ($F(3, 24) = 2.3$, $p = .1$, $\eta_p^2 = 0.2$). So response times did not depend on the target location.

Analysis. Only correctly answered trials were included in the response time analysis. To reduce the influence of outliers in the response times we calculated the median response times for each participant. Error rates were generally low, indicating that participants were able to perform the task accurately (mean error rate 1.1% ± 1.2% (*SD*) target movable and mean error rate 1.3% ± 1.5% (*SD*) target static). Because participants were instructed to minimize the number of errors, the error rates are consequently uninformative and we did not plan any statistical analysis of the error rates. The low percentages of error rates indeed confirm that participants succeeded at answering correctly in most of the trials.

Prior to response time model fitting, we performed an explorative repeated measures ANOVA on the response times with factors target type, target presence, and the number of items.

Search time models. To assess search strategy, each of the four models (introduced in the introduction and described in more detail below) were fitted to the median response times of each participant individually. To determine how well each of our models described the response times while taking into account the differences in the numbers of free parameters, we used the Akaike information criterion (AIC) as well as Bayesian information criterion (BIC). The smaller the AIC or BIC the better the model performs, because these values indicate how much information is lost when a certain function is used to fit the data. The model for which this information loss is the smallest is selected as the best model. Both the AIC and BIC depend on the sums of squares, the number of data points, and the number of free parameters, but BIC penalizes extra parameters stronger than AIC. The *parallel*, *serial,* and *detection without localization* models have 2 free parameters and the *localization after detection* model has 3 free parameters. Because we fitted the models on the individual participants' data, the free parameters are multiplied by the number of participants.

Serial search model. In target present conditions, the target will be found on average after scanning half of the distractors; in target absent conditions, all items have to be scanned in order to be sure that no target is present. The "effective" number of items in target present conditions is therefore 1.5, 2.5, and 3.5 for displays of two, four, and six items, whereas in target absent conditions the effective number of items equals the total number of items. Thus, the slope of the search function in the target present condition will be half the magnitude of that in the target absent condition. The serial search model is a single linear regression with search time expressed as a function of the effective number of items, including both the target present and target absent conditions. To conform to the tradition in the search literature, slopes for the target present conditions will be reported in terms of the total number of display elements; this slope is by definition half of the slope in the target absent condition. This leads to the following search functions with slope *s* (i.e., the increase in time per item) and intercept *t*1 (i.e., the time for one item). These parameters are the same for both the target present (Equation 1) and target absent (Equation 2) conditions:

$$\mathrm{RT}_{present}(n) = t_1 + (n - 1)s \quad (1)$$

$$\mathrm{RT}_{absent}(n) = t_1 + (n - 1)2s \quad (2)$$

Parallel search model. In parallel search, the slope of the search function in target present conditions is 0, because the search time stays the same, independent of the number of items in the display. However, in target absent conditions, the search times go up a little, in a nonlinear way, with the number of items, because the search time for each item varies from trial to trial. In the target present condition, this does not influence the overall search time; the overall average search time equals the average search time of an individual finger, because searching stops as soon as the search time elapses for the finger under which the target is found. In the target absent condition, this is not the case; to be sure that no target is present, a decision can only be made when processing has finished for all fingers. Thus, the overall search time depends on when processing has finished for the slowest finger.

To fit this parallel search model to data, we reason as follows: The distribution of the longest reaction time (RT) of *n* fingers can be found by taking the *n*th power of the cumulative distribution of the times of an individual finger. If we assume that the processing times that each finger needs are distributed normally (standard deviation) around the median and mean ($\bar{t}$), the median RT of *n* fingers (RT(*n*)) for when a target is present and when it is absent are given by Equations 3 and 4, respectively:

$$\mathrm{RT}_{present}(n) = \bar{t} \quad (3)$$

$$\mathrm{RT}_{absent}(n) = \bar{t} + \acute{o}\sqrt{2} \cdot erf^{-1}\left[-1 + 2^n\sqrt{0.5}\right] \quad (4)$$

Thus, for the parallel search model, we need to fit two parameters, $\bar{t}$ and σ, of which only $\bar{t}$ is relevant for the target present condition.

Detection without localization model. The main assumption of this model is that participants can decide whether or not there is a target present somewhere in the display, without the need to localize it. Target present and target absent search slopes and intercepts are therefore identical. In such a case the increase in response time per item is not driven by having to search all possible target locations, but rather a signal to noise ratio, which decreases when the number of distractors increases. This model has only two degrees of freedom: 1 slope and 1 intercept.

$$\mathrm{RT}(n) = t_1 + (n - 1)s \quad (5)$$

Localization after detection model. The main assumption in this model is that localization is a second step in the search process. When participants are asked to localize the target, a localization process will come into effect after the detection process has finished. In target absent conditions, localization does not take place and therefore does not influence the search slope, which will be the same as in the detection without localization model. However, in target present conditions, the additional localization process will cause longer search times and therefore result in larger target present slopes as compared to the target absent slopes.

$$\mathrm{RT}_{absent}(n) = t_1 + (n - 1)s_a \quad (6)$$

$$\mathrm{RT}_{present}(n) = t_1 + (n - 1)s_p \quad (7)$$

where $s_p > s_a$.

In all models, $\bar{t}$ or t_1 represents the intercept, which is the average time required to process one item in the display. This depends only on the difficulty of identifying the items presented.

Results and Discussion

Figure 2 shows that the response times increase with the number of items. However, the response times for target present and absent trials were comparable. Moreover, the response times of the two conditions (target static and target movable) were similar. A repeated measures ANOVA on the RTs showed an effect of the number of items ($F(2, 22) = 29.3$, $p < .0001$, $\eta_p^2 = 0.78$), no effect of target presence nor any interaction effects ($p > .5$). The effect of target type was close to significance ($F(1, 11) = 4.33$, $p = .062$, $\eta_p^2 = 0.28$).

Comparison of the AICs and BICs for each of the four models introduced in the Method section indicated that the detection without localization model performed best for both the target static and target movable conditions (see Table 1). Slopes of the detection without localization model fit were 34.5 ± 5 and 35 ± 5 (*SE*) ms/item for static and movable respectively. Slopes did not differ significantly between target static and movable, $t(11) = -.17$, $p =$

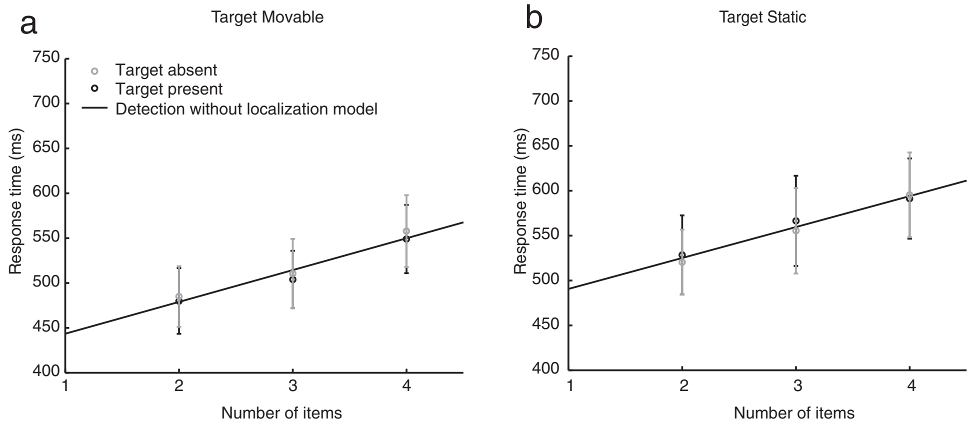

Figure 2. Results, Experiment 1: Response times averaged over participants and the best performing model fits (detection without localization) as a function of the number of items for target present and absent trial. (a) Target fixed, (b) target Movable. Error bars represent the standard error of the mean (*SE*).

.86. Intercepts were 456 ± 34 and 408 ± 35 (*SE*) ms, where the target static intercept was significantly larger than target movable, $t(11) = 4.2$, $p = .0014$.

Our results show that response time slopes did not differ between the target static and target movable conditions, indicating equal search slopes. For both conditions the detection without localization model described the data best. This model describes the most efficient search behavior and suggests that participants detected the target without the need to examine the individual fingers. This resulted in comparable search times and search slopes for target absent and target present trials. Furthermore, search slopes did not differ between the target static and target movable conditions. This means that there was no search asymmetry and thus a static target among movable distractors was detected with the same efficiency as the inverse condition.

Given existing literature on haptic search it is surprising finding that the detection without localization model described the data best. Usually in haptic search tasks the target absent slope is found to be larger than the target present slope (Lederman & Klatzky, 1997; Overvliet et al., 2007; Plaisier et al., 2009b; Van Polanen et al., 2012a). In the (Overvliet et al., 2007) study where the parallel and serial search models were introduced, a very similar task to the one reported here was performed, with the exception that participants had to lift the finger at which the target was located. Such an experimental design forced the participants to localize the target, whereas in the current study this step could be skipped. This additional task of having to localize the target might account for the difference in results. However, an alternative hypothesis would be that search for a movable part is performed with a different search strategy than search for a raised line pattern (as was used in the Overvliet et al. (2007) study), and therefore leading to a deviating pattern. We tested these hypotheses in Experiment 2. In order to do so we used an experimental design that was very similar to that of (Overvliet et al., 2007).

Experiment 2

Method

Participants. Twelve participants took part (mean age 22.4 ± 1.6 (*SD*) years, all right-handed according to the Edinburgh Handedness Inventory (Oldfield, 1971). Six of them had previously participated in Experiment 1.

Stimuli & apparatus. The same experimental set-up as in Experiment 1 was used. The stimuli were also the same as in Experiment 1 except that only the target-fixed condition was used.

Procedure. The procedure was largely the same as in Experiment 1, except that participants had to report under which finger the target was located. In order for them to do so we labeled the fingers 1 to 4 from the index finger to the little finger. This method has been used previously to investigate localization in haptic search (Purdy et al., 2004). On target present trials participants had

Table 1
Model Fit Performance in Experiment 1 (The Relative Likelihood is Shown in Parentheses)

Condition	Statistic	Model: Parallel	Serial	Detection without localization	Localization after detection
Target Movable	AIC	560.8 (<.0001)	527.4 (.021)	519.2 (∼1)	551.2 (<.0001)
	BIC	615.5 (<.0001)	582.0 (.021)	574.3 (∼1)	633.2 (<.0001)
Target Static	AIC	582.3 (.0001)	576.0 (.0016)	563.1 (∼1)	576.5 (.0012)
	BIC	637.0 (.0001)	630.6 (.0016)	617.7 (∼1)	658.4 (<.0001)

Note. AIL = Akaike information criterion; BIC = Bayesian information criterion.

to call out the number of the finger under which the target was located, and in target absent trials they simply answered ‘no.” Again they had to do this as fast as possible, but also try to be correct.

Analysis. Data analysis was the same as in Experiment 1. Error rates were generally low, indicating that participants were able to perform the task accurately (mean error rate 1.4% ± 1.2% (*SD*)).

Results and Discussion

In Figure 3 it can be seen that the response times were comparable to those found in Experiment 1. In the target present trials, however, the response times do seem to increase faster with the number of items than in the target absent trials. A repeated measures ANOVA on the RTs showed an effect of the number of items ($F(2, 22) = 43.5$, $p < .0001$, $\eta_p^2 = 0.80$) and of target presence ($F(1, 11) = 12.0$, $p = .005$, $\eta_p^2 = 0.52$), and an interaction between target presence and number of items ($F(2, 22) = 7.6$, $p = .003$, $\eta_p^2 = 0.41$).

Search strategy was again assessed by model comparison. Table 2 shows the goodness of fit variables for each of the four models tested. The localization after detection model performed best resulting in the lowest AIC and BIC. The intercept of the model was 483 ± 44 (*SE*) ms and the slopes 44 ± 7 and 72 ± 6 ms/item for absent and present respectively. The slope of target present was significantly steeper than the slope of target absent, $t(11) = 5.6$, $p = .0002$.

In contrast to Experiment 1, we found a difference between the target present and absent search slopes in Experiment 2. This is confirmed by the finding that the Localization after detection model described the data best (this model has two independent slopes for target present and absent and a fixed intercept). The target absent slopes were similar to the slope found in the target fixed condition of Experiment 1 (Experiment 1: 34.48 ± 62.98 (*SD*) ms/item and Experiment 2: 44.40 ± 32.64 (*SE*) ms/item; $t_{df22} = .48$, $p = .63$)). This shows that asking participants to report under which finger the target was located affected the target present trials and (logically) not the target absent trials. These results suggest that participants first detected whether there was a target and subsequently localized the target (in target present trials).

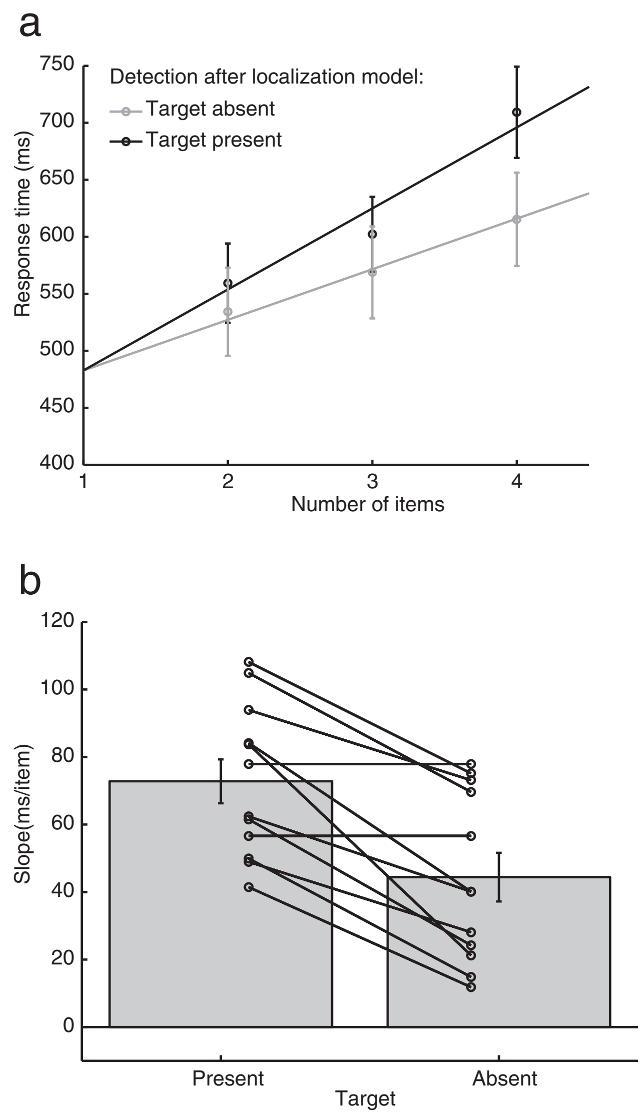

Figure 3. Results, Experiment 2: (a) Response times averaged over participants and model fit of the best performing model (localization after detection) as a function of the number of items for target present and absent trial. (b) The resulting slopes from the fits on the individual participants' data. Bars represent the mean across participants and the circles are the individual participant slopes. Error bars represent the standard error of the mean (*SE*).

Discussion

In Experiment 1 we found similar response times for target present and target absent trials. The finding that the detection without localization model described the data best suggests that participants detected the presence or absence of a target with equal efficiency and possibly without localization. When participants were asked to localize the target in Experiment 2, we found that the localization after detection model described the data best. This suggests that the localization step was implemented independent of detection and only when a target was detected.

The parallel and serial search models assuming localization prior or simultaneously to detection as introduced by Overvliet et al. (2007) did not describe the data very well in neither of our experiments. This is despite the fact that Experiment 2 was designed to be very similar in task description to that previous study. However, the raised line stimuli used by (Overvliet et al., 2007) were quite different compared to the current experiment. Relative movability as used in the current study leads to clearly different search behavior. Our finding that the detection without localization model performed best suggests that in our experimental setting, the target could be detected without localizing it. Moreover, when participants were asked to localize the target, they clearly seemed to do so after the target was detected in an additional processing step.

In the current study, adding the task of localizing the target led to an increase in response time slope. In a previous study by Purdy et al. (2004) in which participants were asked to localize the target

Table 2
Model Fit Performance in Experiment 2 (The Relative Likelihood is Given in Parentheses)

Condition	Statistic	Model: Parallel with localization	Serial with localization	Detection without localization	Localization after detection
Target Static	AIC	643.0 (<.0001)	645.7 (<.0001)	601.5 (<.0001)	564.3 (~1)
	BIC	697.6 (<.0001)	700.4 (<.0001)	656.1 (.0074)	646.3 (~1)

Note. AIC = Akaike information criterion; BIC = Bayesian information criterion.

in the same way as in the current study, no such systematic increase of slope due to target localization was found. This was the case for a range of different haptic features, but movability was not included. One could argue that the target present slope increase was due to an increase in possible responses (2, 3 or 4) instead of localization per se. If this were the case then the difference between target present and absent slopes should also have been present in the study of Purdy and colleagues. That is not the case, indicating that the target present slope was really due to having to localize the target. In haptic search studies where it is found that target absent trials are larger than target present trials, localization was most likely not performed after detection. So this suggests that for example in the study of Van Polanen et al. (2012a) target detection was accompanied by or preceded by target localization. This might mean that the search strategy reported in the current study is specific to detection of relative movement.

A second finding indicating that indeed the detection of relative movement might be different from detection of other feature differences is the fact that we did not find a search asymmetry. In other words, search for a fixed target among movable distractors was performed with the same efficiency as the reverse condition. Most studies into haptic search have reported search asymmetries for features such as roughness, edges, or compressibility (Lederman & Klatzky, 1997; Overvliet, Smeets, et al., 2008; Plaisier et al., 2008, 2009b; Van Polanen et al., 2012b). Search asymmetries can be caused by feature differences being at opposite ends of an intensity scale. For instance, finding a rough item among less rough items is easier than the reverse case. The absence of a search asymmetry in the current study suggests that participants simply detected whether there was relative movability anywhere in the display. Whether the target was movable or static, if a target was present there should be one finger moving next to a finger that was static anywhere in the display. If participants used this cue, a search asymmetry would not be expected.

The search strategy found in the current study appears to be specific to the movability feature. Only a few other studies have looked at haptic perception of movability. For example, movability facilitated haptic discrimination of objects from the background (Pawluk et al., 2010, 2011). This is consistent with our hypothesis that movability is detected efficiently such that it can be used to decide which parts belong together. Van Polanen and colleagues asked participants to move their hand over a display on which there were spheres that could rotate. Also in that study it was concluded that search for movability was highly efficient (Van Polanen et al., 2012a). However, in contrast to the current study, the target absent slopes were found to be larger than the target present slopes, and there was a search asymmetry. This is most likely caused by the forced serial character of exploring a 2D display, as compared to our simultaneous presentation of the stimuli.

In sum, we have shown that haptic search strategies can differ in more aspects than simply parallel versus serial. For some features, at least for movability, a target seems to be detected in a single step without having to localize the target. Localization of the target was done as a second step after detection has been accomplished, resulting in an added task load and an increase in target present slopes. Overall, we can conclude that detection of movability is performed efficiently fitting with the idea that detection of movability is crucial for handling objects.

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