Remember the good vibes! The fragile nature of tactile memory and its implication for the design of body-centric vibrotactile displays.

Despite its enormous importance for the design of multi-modal interfaces, tactile perception remains an under-researched domain in HCI as compared to the auditory and visuo-spatial modalities. To make progress, we aim to address contradictory findings of prior research on the storage capacity of tactile short-term memory (tSTM). Applying a modified delayed match-to-sample paradigm and performing a model-based analysis, the results suggest a noisy signal detection process to underlie tactile perception. In contrast to the visual or auditory domain, however, a more accurate high-threshold detection process does not seem to contribute substantially. Thus, our study lends evidence to tactile representations that are prone to feature overwriting and interference, severely limiting tSTM's storage capacity. We conclude with a discussion on how these findings may inspire the design space of vibro-tactile interfaces taking into account the fragile nature of tactile perception and touch.

CCS Concepts: • **Human-centered computing → Ubiquitous and mobile computing**; **Ubiquitous and mobile computing theory, concepts and paradigms**;

Additional Key Words and Phrases: tactile sense, vibro-tactile display, tactile memory, signal detection model

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1 INTRODUCTION

So far, HCI had its main focus on developing interfaces that support the processing of visuo-spatial and auditory information. One major reason is probably the fact that the storage and processing capacity of our cognitive system is larger in the visuo-spatial and auditory than in other modalities, such as the tactile modality. Strong empirical evidence comes from research on tactile short-term memory (tSTM) [3] demonstrating that the storage capacity of tSTM is very limited and not much larger than two items (i.e., tactile representations). Nevertheless, there is no doubt about the importance of interfaces that involve different senses and can convey information e.g. using external representations that can be sensed via tactile perception. Only in this way will it be possible to design radically new interfaces, which do justice to essential characteristics of human cognition, such as the embodiment of mind, and which realize an effective offloading of the visual and auditory modality.

In fact, we see a growing interest for body-centric vibro-tactile peripheral interactions for various applications, including mindfulness[8], emotional regulation[9], notifications[20], spatial navigation[25] and more. Such interest can be largely explained by the need to offload cognition from visual and audio modalities, distributing it to tactile sense.

What properties should an interface have to facilitate interaction on the periphery of a user's attention? In addition to communicating information without effort and acting gently in the background, it must carry information about the context (e.g. temporal, semantic, emotional) which can be easily retrieved by a user[16, 26].

Natural haptic information (i.e., active touch, such as manipulating a 3D object) is much more robust and most of the time processed on a periphery of our attention while giving us contextual information (e.g., personal experiences associated with an everyday object) without a user's attentional effort. This works differently for passive (i.e., tactile) touch[15, 22]. Therefore, body-centric vibro-tactile displays have greater limitations in terms of how they are perceived by a human and how much contextual information they may carry.

Despite of a growing interest in designing vibro-tactile interfaces, prior research on how tactile stimuli are perceived and remembered is focused on the storage and processing capacity of memory for touch. Thus, typical research questions refer to the number of tactile stimuli that can be maintained, to the duration of maintenance, or to the processes of interference and decay that determine the capacity and duration. However, to the best of our knowledge, none of these studies deals with the quality or nature of the representations underlying tactile perception and memory. In the visuo-spatial and auditory domain, by contrast, this question has been intensively investigated, and a large body of experimental research (e.g., [10, 21, 27, 29]) has found evidence of a so-called dual-process account of processing, maintaining and recalling items (e.g., faces or words). This account of human memory judgments assumes two qualitatively distinct processes to underlie memory judgments, namely

- Familiarity (*F*), operating on a continuous dimension of memory strength and reflecting a sense of oldness (e.g., somehow knowing that I have met this person before), and
- Recollection (*R*), denoting a discrete (all-or-none) retrieval process that comes along with the vivid reinstatement of qualitative information about the 'learning' episode (e.g., remembering the time and place of a party where I have got to know a person).

While familiarity is based on memory representations that mainly allow to retrieve quantitative memory strength, the representations underlying recollection also allow to retrieve qualitative context information, such as the music or other guests of a party.

If we look at prior research in HCI, we see many examples where the dual process account is utilized in the visual [14, 24] and auditory [7, 19] modality based interfaces for peripheral communication. Such interfaces aim to unobtrusively convey information about the context which can be easily retrieved by a user. This is possible due to the existence of two independent memory processes involved in auditory and visual senses. Determining whether only one process (familiarity) is involved or whether a second (recollection) contributes as well, significantly influences the design space, user applications and cross-modality interaction design aspects.

Therefore, the main motivation of our research endeavor is to further our understanding of the properties and limitations of tSTM. In particular, the present paper focuses on the question of whether the existence of two distinct types of processing and corresponding forms of memory representations — one being noisy but cognitively effortless, the other being accurate but cognitively effortful — can be evidenced also for tactile perception and memory.

From our viewpoint, the question of whether such a dual-process account also applies to the tactile domain of human cognition is crucial for stimulating new ways of thinking about novel design ideas. Depending on the answer that we may find, we will know if a tactile display can interface with and target a cognitive subsystem that can draw on either a robust and reliable memory for vibes and touch or needs to get along with rather fragile and noisy traces of environmental stimulation.

In the following, we provide a brief overview of related work that has lead to the present research questions. We then outline our methods and describe and discuss the main findings. We finally conclude with a reflection on some limitations that will motivate future work and follow-up experiments.

2 RELATED WORK

2.1 Prior work on the capacity of tactile short-term memory

Prior HCI research on tactile displays has been drawing on cognitive research on memory for tactile touch (for a review see e.g. [12]). The reason is the well-established finding that perception and memory share the same neurophysiological correlates (e.g., [1]). The consequence is that experiencing something is always grounded in a blend of new environmental stimulation and the retrieval of similar episodes experienced in the past (e.g., [6]).

A prominent line of research on tactile memory is represented by work of Gallace and colleagues[11–13], examining the memory's storage capacity, i.e., the number of tactile representations that can be maintained and recalled, as well as the representations' duration. Inspired by Sperling's research on the capacity of iconic memory (i.e., sensory memory for visual items; e.g.,[23]), Gallace and colleagues apply a full vs. partial report paradigm to estimate storage capacity. A set of six tactors is distributed across a participant's body surface, and in each experimental trial, a subset is brought to vibration. Under the full report condition, the participant must provide a numerosity judgment on the total number of tactors that have vibrated. Under the partial report condition, one of the six tactors is sampled and the participant must indicate whether the sample was among the trial's subset. The comparison of the two conditions results in an estimate of up to five items – a storage capacity comparable to that of the echoic sensory memory store (e.g.,[10, 18, 29]). However, as pointed out by the authors themselves[11–13] and other researchers (e.g., [15]), these results need to be interpreted with caution. In particular, the applied paradigm does not allow to separate contributions from a peripheral (i.e., purely tactile) from the contributions of a more central (working memory) system. Thus, it is not clear whether participants' performance relies on the processing of tactile representations only or whether higher-level cognitive processes, such as visuo-spatial and verbal recoding, are in play as well.

A paradigm that allows to attribute memory judgments more directly to the tactile short-term memory (tSTM) is the delayed match-to-sample paradigm (DMS). It has been applied repeatedly by Bancroft and colleagues (e.g., [2–4]) and includes the presentation of a sequence of three tactile stimuli at the index finger: A target T1 with a particular frequency (e.g., 22Hz) is followed by a second target T2 with a different frequency (e.g., 30Hz) and a probe P, which is either identical to one of the two targets (e.g., 22Hz; *Same* condition) or differs from both of them (e.g., 18Hz; *Different* condition). The participant needs to compare P to T1 and T2 and to respond with 'same' and 'different' under the *Same* and *Different* condition, respectively. By keeping the location of stimulation constant, the DMS allows to derive estimates of tSTM's capacity, which are relatively less affected by more central types of processing, such as verbal recoding.

Based on DMS data, Bancroft and colleagues have developed a cognitive-computational model of tSTM (e.g., [4, 5]). It assumes two layers of neurons situated in the prefrontal cortex, which are interconnected in form of circuits. In each of these circuits, the first layer consists of a 'comparison' unit C, whose initial firing rate is a monotonic function of the frequency of a target (e.g., T1). Through excitatory connections, the C unit passes this level of activation to the second layer, where it gets stored in form of a 'memory' unit M. Later on, inhibitory C-to-M connections allow to subtract this stored information from a new activation level in C, which is evoked by the new stimulus P. Thus, the final firing rate of the C unit allows to compare the frequencies of the target and the probe as this rate will be close to/significantly above zero, if the two stimuli have the same/have a different frequency. Because there is a large number of such circuits, the network can draw on an average firing rate across layer C and can compare it to a threshold θ. The network will respond with 'different', only if the average firing rate exceeds this threshold.

2.2 A signal detection account to explore the nature of tactile short-term memory representations

In our opinion, Bancroft's cognitive-computational model of tSTM [4, 5] describes a judgment process that memory psychology typically characterizes as a neo-cortically mediated familiarity signal formalized as a Gaussian signal detection process (e.g., [27, 28]). Using the terminology of a standard signal detection model (SDM; e.g., [17]), the probes of *Same* trials lead to a normal distribution of familiarity or novelty values with a mean of zero and a standard deviation of 1 along a decision continuum. The probes of *Different* trials cause higher novelty values and thus a normal distribution shifted to the right with a mean of M_D and a standard deviation of SD_D. Again, a decision criterion denoted c is needed to differentiate the two distributions. The distance between the two means corresponds to the sensitivity of a person, usually measured in z units and denoted d'. Note that at this point we deviate from a standard SDM in that the decision continuum does not represent a familiarity but an inverse novelty strength. We deliberately make this deviation in order to translate Bancroft and colleagues' model assumptions as directly as possible into an SDM.

According to these model assumptions, a person makes a Hit (i.e., responds with 'different' in a *Different* trial) and a false alarm (FA; i.e., responds with 'different' in a *Same* trial), if the novelty signal exceeds the criterion in a *Different* and *Same* trial, respectively. Thus, $P(\text{Hit}) = \Phi(d'/2 - c)$ and $P(\text{FA}) = \Phi(-d'/2 - c)$.

If the model of Bancroft and colleagues were complete with respect to the cognitive processes involved in recalling tactile frequencies, this formalism should already be sufficient to accurately predict participants' DMS responses. A conventional way to empirically test whether this is indeed the case is to collect data for a Receiver Operating Characteristic curve (ROC) and to check the model's ability to account for it. An ROC results from drawing Hit against FA rates as a function of participants' response confidence (see Figure 1). For this reason, we have slightly extended the DMS and instructed the participants to rate their confidence in their 'same' and 'different' responses on a four-point Likert scale.

2.3 Research Questions and Hypothesis

The first research question arising from the above is:

- Does a single-process signal detection model (SDM) account for the average shape of an ROC to be observed in a DMS paradigm? (RQ1)

Given that our DMS account sufficiently reflects the assumptions of the empirically validated model of Bancroft and colleagues, our first hypothesis is that the answer to RQ1 is yes (Hypothesis 1).

As already stated in the introduction, studies on the recognition of visual (e.g., [28]) and acoustic items (e.g., [18]) imply that a second memory process called Recollection can contribute. This process takes place in a distinct hippocampal system (e.g., [10]) and allows, by means of more robust representations, an accurate retrieval of qualitative context information accompanied by a high response confidence (e.g., [29]). Typically, recollection is formalized as a discrete threshold process and represented in form of a single probability R. This simply means that a certain proportion of items can be recollected but that others cannot.

Table 1. Sequence of events in one single trial of the DMS paradigm

Target 1	Delay	Target 2	Delay	Probe	Response	Confidence Rating	Break
1000 ms	600ms	1000ms	600ms	1000ms	self-paced	self-paced	optional

If recollection were involved in the recognition of tactile stimuli, a dual-process signal detection model (DPSDM) would result, according to which an FA can only occur when a target is not recollected $(1 - R)$ and the novelty value exceeds the criterion c. Put differently, $P(\text{FA}) = (1 - R)\Phi(-d'/2 - c)$.

So far, it has not been investigated whether this assumption also applies to the recognition of tactile items. Therefore, the second research question is:

- Does a dual-process signal detection model (DPSDM) provide a better fit to an ROC, which can be observed in a delayed match-to-sample paradigm (DMS), than a standard signal detection model (SDM)? (RQ2)

Given that previous research on tSTM has found many parallels to the visual and acoustic domains, our second hypothesis is that the answer to RQ2 is also yes, i.e., that both recollection and familiarity contribute to the recognition of tactile stimuli (Hypothesis 2).

3 METHOD

3.1 Participants

Up to this point we have run the DMS paradigm involving only three participants (2 female participants of age 33 and 54 years old, and 1 male of 45 years old). The large number of data points per participant (i.e., 60 responses under the *Same* and 60 responses under the *Different* conditions), however, allows already now to report relatively robust parameter estimates. Nevertheless, we consider the present data pattern to reflect only preliminary results. That is, we understand the limitations of such a small sample size and continue to collect data up to a sample size of at least twelve participants.

3.2 Apparatus and Procedure

Participants are presented with a vibration pulse on the left index finger, using a voice-coil vibro-tactile tactor (model: TEAX13C02, Tectonic Elements, UK). The actuator is housed in the stretchy material to absorb the noise from the vibration. The index finger is placed on top of the tactor's membrane. The actuator is computer controlled and powered with an audio amplifier (PAM8302). Tactile stimulus is generated as an audio signal and played through the Psychopy experiment interface. The interface is customized to the needs of the experiment, using Python.

The pilot study is an extension of the standard delayed match to sample paradigm and builds upon the study of [3]. The independent variable is the difference in frequency between target(s) and probe. The amplitude is at a constant rate of 50 Db. Each trial consists of three 1000 ms vibro-tactile stimuli, separated by unfilled 600 ms delay periods: two target stimuli (denoted T1 and T2) and one probe (denoted P). The P has either the same frequency as Target 1 or Target 2, or it differs from both. If the P frequency is different from the target stimuli, it is separated from both targets by 5 Hz, or separated from one target by 5 Hz and from the other by 15 Hz. The frequencies of T1, T2 and P are 42, 47, 52, 57, 62 Hz. The target items are always of different frequencies, differing by 10 Hz. Each scene is presented as a single vibration pulse. We tested the following four conditions: (1), where the P's frequency is the same as that of T1 (ST1); (2), where the P's frequency is the same as that of T2 (ST2); (3) where, the P's frequency is different from the frequencies of both

Table 2. Confusion matrix underlying the empirical ROC curve of Figure 1

Trial type	'different'				'same'				Total
	'4'	'3'	'2'	'1'	'1'	'2'	'3'	'4'	
Different	32	39	22	9	9	23	31	15	180
Same	16	19	28	22	15	20	47	13	180

T1 and T2, being 5 Hz away from T1 and 15 Hz different from T2 (DT1); (4) where, the P's frequency is different from the frequencies of both T1 and T2, being 15Hz away from T1 and 5 Hz away from T2 (DT2) - 30 trials;

Subjects are presented with 120 trials: 60 *Same* and 60 *Different* - probe trials. There are equal numbers of *Same* - frequency probe trials (ST1 and ST2, 30 per condition), and equal numbers of *Different*-frequency-probe trials (DT1 and DT2 trials, 30 per condition). At the end of each trial participants, are tasked to respond "same" (by pressing the 's' key on the keyboard) if the probe matched either of the target stimuli. If the probe does not match either of the target stimuli, they are instructed to respond "different" (by pressing the 'd' key). After the response, the participants are instructed to rate on a scale from 1- 4 (1-not confident at all; 4 - absolutely confident) how confident they are in their response. The experiment is self-paced. Table 1 represents the sequence of events making up one single trial. Before the actual experiment, the participants completed a short (40 trials) practice session, which is similar to the actual study, with minor deviations: the duration of the targets and probe is 1500 ms and the participants receive feedback on their response accuracy.

3.3 Data Collection and Analysis

To prepare the data for our ROC-based model analyses, we counted participants' responses according to the so-called confusion matrix, which cross-tabulates trial type by response category. Table 2 presents the observed frequencies for each of the resulting cells of the matrix after aggregating the responses of all three participants.

4 RESULTS

4.1 Descriptive analysis

The left diagram in Figure 1 shows the empirical ROC curve (black-filled dots) that is based on the aggregated data (see the confusion matrix presented in Table 2) and plots the sample's performance (Hit-FA pairs) as a function of response confidence. The plotted probabilities are obtained by cross-tabulating trial type (*Same* vs. *Different*) with the eight response categories (4 confidence categories for *Same* and *Different* trials) and dividing each cell frequency by the total number of trial type presentations (60 presentations * 3 participants). The empirical ROC is based on the cumulative conditional probabilities, resulting in a probability of 1 for the eighth category, which is therefore not included.

In general, the empirical ROC exhibits a convex shape that can typically be observed in experiments on memory for visual and auditory stimuli: It increases gradually in a curvilinear manner and approaches the 1,1 intercept ([10, 27]). Furthermore, it is asymmetrical along the minor diagonal, indicating different standard deviations (*SD*s) of the underlying *Same* and *Different* distributions. When performing a z-transformation of the probabilities (see the diagram in the middle), a linear relationship with a slope s smaller than 1 results ($s = .78$; $R^2 = .98, p < .001$). This means that the two underlying distributions (see the right diagram) are normally distributed (as indicated by the linear relationship) and that the *SD* of the *Different* distribution is larger than the *SD* of the *Same* distribution (as indicated by $s < 1$). In

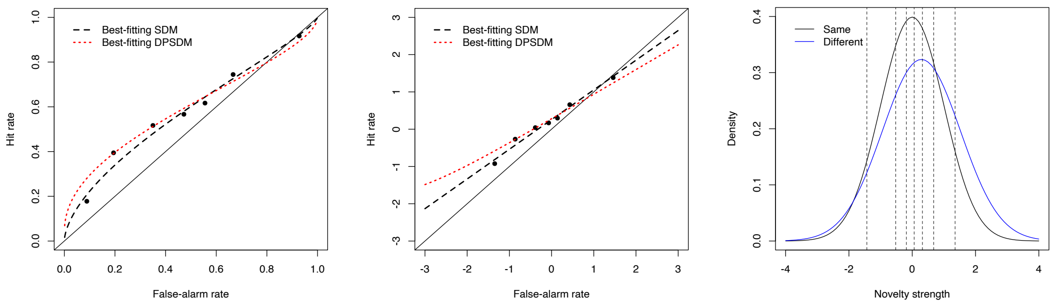

Fig. 1. ROC curves and best-fitting SDM and DPSDM on linear and z coordinates (left and middle diagram, respectively) and underlying distributions of novelty strength for 'Same' and 'Different' trials under the assumption of an SDM (right diagram).

Table 3. Summary of model-based analyses drawing on the standard signal detection model with unequal variances (SDT) and the dual-process signal detection model (DPSDT)

Model	R	d'_2	A_z	*SD* ratio	*df*	χ^2	p
SDT	-	0.26	.58	.80	5	2.27	.811
DPSDT	.03	0.31	.60	.64	4	5.27	.261

particular, the ratio is 0.78:1, which comes very close to the average ratio of 0.80 reported in the visual and auditory domains (e.g., [27]).

The convex shape of the empirical ROC on the left further reveals a response behavior above chance. At the same time, we can see clear signs of a difficult discrimination task, i.e., of a rather small sensitivity of the participants. For instance, we can observe a relatively small area under the ROC curve in the left diagram ($A_z = .58$), reflecting a relatively small distance between the means of the underlying density distributions (right diagram). When measured in z units, this distance corresponds to the sensitivity measure d'_2, which is given by the intercept of the z-transformed ROC at $z(F) = 0$ (e.g., [17]) and is $d'_2 = .26$. Note that random response behavior would be indicated by $d'_2 = 0$. This outcome is well in line with findings of [3–5], who also applied the DMS paradigm and found tactile memory representations to be extremely prone to processes of interference and decay.

4.2 Model-based analysis of RQ1

These results already indicate that the main assumptions of the standard (unequal-variance) signal detection model (SDM) are compatible with data from the DMS paradigm. To also examine our first research question quantitatively, we fitted the model against the empirical ROC (see the dashed black lines in the left and middle diagram of Figure 1). While the plots already suggest that the model fits the data well, this impression is further supported by the corresponding statistical parameter estimates presented in Table 3. In particular, the small χ^2 value means that the deviation between the empirical data points and the theoretical curve is not significant and that the model can account for a substantial amount of variance in participants' response behavior. In the sense of our first hypothesis, this outcome therefore lends evidence to our signal detection-based interpretation of Bancroft and colleagues' cognitive-computational model of tactile short-term memory.

Though this goodness-of-fit is already appropriate, we now turn to our second research question and examine whether integrating a discrete threshold process (Recollection) further improves the model.

4.3 Model-based analysis of RQ2

To examine our second research question, we have also fitted the dual-process signal detection model (DPSDM) to the empirical ROC. A glance at the left and middle diagram reveals that the DPSDM (represented by the dashed red lines) does not account for the data as well as the standard detection model (SDM). Though the DPSDM includes the additional parameter *R*, its goodness-of-fit seems to be smaller than that of the SDM. In particular, when comparing the two models' χ^2 estimates, the resulting difference is significant at the 10% level, $\chi^2(1) = 3, p = .083$.

In summary, both the smaller number of parameters and the higher goodness-of-fit speak in favor of a single process model. Against our second hypothesis, we therefore conclude that memory for tactile stimuli in the DMS paradigm only relies on one process, namely familiarity. The contribution of Recollection seems at best very small (see the estimate of *R* in Table 3) and negligible in terms of modelling the data.

5 CONCLUDING REMARKS AND FUTURE WORK

In this paper, we report preliminary results from an ongoing experiment that aims at investigating properties of tSTM, particularly, the quality of tactile representations that underlie memory judgments in a DMS paradigm. The present findings provide evidence of a single process model, which assumes a rather noisy Gaussian detection mechanism. According to [10], such a mechanism reflects a certain type of representation that can store only quantitative information, namely a strength or sense of familiarity, and is realized by neo-cortical cell assemblies. Thus, the results are in line with the cognitive-computational model of Bancroft and colleagues [2, 4, 5], which also assumes a single decision process subserved by prefrontal neural populations and superimposed by substantial noise (e.g., through "irrelevant sensory input" or "background neural activity").

Contrary to our second hypothesis, we have so far found no evidence for a second type of representations that allow the recollection of qualitative context information about an episode and thereby judgments of high accuracy and confidence. In brief, the present results favor a single over a dual-process account of tSTM and point towards the existence of tactile representations, which are prone to feature overwriting and interference, severely limiting tSTM's storage capacity.

Before outlining potential design implications and plans for our future work, we would like to stress that we will continue to collect data and conduct follow-up experiments to test these conclusions more stringently. In addition, we are aware that different results might be observed if another paradigm was used (e.g., see the partial versus full report paradigm described in Section 2). This has to be investigated further.

If, using both paradigms, the results converge, it will clarify and impose certain design and application constraints for vibro-tactile displays. For instance, it will be justified to say that due to fragility of tactile perception, a vibro-tactile display on its own will not be suitable for off-loading the cognition where contextual information is to be conveyed. The desired offloading will not happen due to recoding tactile representations by means of other modalities.

For a novel, first time vibro-tactile stimuli, the peripheral interaction may happen only on the physiological level, where valence and arousal states are influenced. Thus, many vibro-tactile applications already utilize the ability of tactile stimulation to manipulate the affective states of a human without registering it consciously[8, 9]. On the other hand, prior work shows that tactile sense can play an important role in multi-modal interactions by enhancing the experience, shortening learning curve and more. A novel approach would be to use a vibro-tactile device to activate a holistic system of associations, acting as a primer for enhancing or triggering the representations in other modalities for intended psycho-physiological states (e.g. in cognitive-behavioral therapies).

Understanding the complex interplay between vibro-tactile design parameters (e.g., frequencies, amplitude, duration, body site) and other modalities and how this influences the perception and affective state of a user is an ongoing challenge. We plan to focus our future research in this direction.

6 ACKNOWLEDGMENTS

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