Evaluating Visuohaptic Integration on Memory Retention of Morphological Tomographic Images

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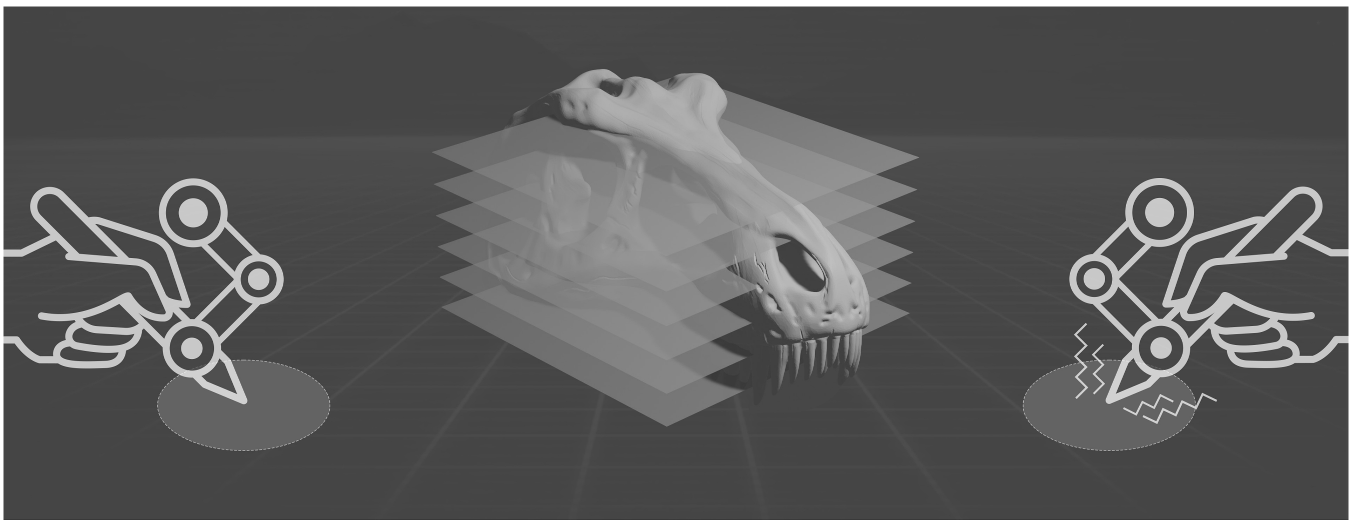

Figure 1: Our study compares visual and visuohaptic sensory modality encoding conditions on memory retention of tomographic images. Results indicate that visuohaptic integration enhances retention, reducing error rates and shortening response times.

Abstract

Scientific visualization and tomographic imaging techniques have created unprecedented possibilities for non-destructive analyses of digital specimens in morphology. However, practitioners encounter difficulties retaining critical information from complex tomographic volumes in their workflows. In light of this challenge, we investigated the effectiveness of visuohaptic integration in enhancing memory retention of morphological data. In a within-subjects user study (N=18), participants completed a delayed match-to-sample task, where we compared error rates and response times across visual and visuohaptic sensory modality conditions. Our results indicate that visuohaptic encoding improves the retention of tomographic images, producing significantly reduced error rates and faster response times than its unimodal visual counterpart. Our findings suggest that integrating haptics into scientific visualization interfaces may support professionals in fields such as morphology, where accurate retention of complex spatial data is essential for efficient analysis and decision-making within virtual environments.

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CCS Concepts

• **Human-centered computing → Human computer interaction (HCI)**.

Keywords

Haptics, Visuohaptic Integration, Feedback, Data Analysis, Data Exploration, Human-Computer Interaction, Mental Representations, Working Memory

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1 Introduction

In morphology, the study of form and structure of organisms has been revolutionized by recent developments in imaging and visualization technologies, enabling practitioners to create highly detailed digital models of fossils for non-destructive specimen analysis [Cunningham et al. 2014; Racicot 2016]. However, despite the transformative impact of digital methods on morphology, interacting with tomographic fossil data remains complex and labor-intensive. Automated imaging processing methods are seldom suitable for paleontological datasets due to their complexity and the challenge of applying generalized models to highly variable fossil specimens [Carvalho et al. 2020; Toulkeridou et al. 2023]. Consequently, morphology researchers must manually process regions of interest across numerous tomographic slices, which places significant cognitive demands on spatial understanding and memory retention [Maga 2023; Siqueira Rodrigues et al. 2023].

One of the most cognitively demanding requirements in the digital morphology workflow is the ability to mentally represent and accurately interpret the spatial features of 3D structures based on their 2D cross-sections [Carroll 1993; Elewa 2013]. Morphologists must retain detailed mental representations of tomographic slices and infer the relationships between different slices and viewpoints of specimens [Ziegler et al. 2010]. These practitioners often rely on mental representations to make informed decisions as they work across tomographic slices, requiring precision and robust retention of the spatial relationships within the data [Pandolfi et al. 2020]. Traditionally, these manual tasks have been performed through vision-only interactions on desktop setups [Sutton et al. 2016], which may not fully support the cognitive demands of cross-sectioning, potentially leading to errors and inefficiencies [Siqueira Rodrigues et al. 2023].

The literature suggests that combining touch and vision coherently could enhance cognitive tasks involving interaction with digital objects [Kaas et al. 2007; Newell 2010]. As these senses share an established cognitive synergy, visuohaptic integration might improve the robustness of digital object representations [Amedi et al. 2001; Easton et al. 1997b]. Previous research demonstrated that integrating congruent haptic feedback with visual information can enhance memory retention for synthesized 3D objects across the virtual reality continuum [Siqueira Rodrigues et al. 2024a,b]. However, limited knowledge exists on whether these benefits extend to the complex, real-world data encountered in morphology tasks. As the characteristics of morphological data could interfere with the synergistic effects of visuohaptic integration and produce negative outcomes, it is crucial to investigate whether previously observed haptic enhancement effects translate into this use case.

This paper addresses this gap through a within-subject study that investigated whether visuohaptic integration improves memory retention of morphological data in a delayed match-to-sample task (DMTS), which is a well-established method for exploring cognitive processes involved in the retention of visual [Harrison and Tong 2009; Romo et al. 1999], haptic [Schmidt and Blankenburg 2018; Schmidt et al. 2017], and visuohaptic stimuli [Siqueira Rodrigues et al. 2024b]. Our DMTS task comprised a learning phase where participants encoded tomographic slices of fossil specimens presented in visual or visuohaptic conditions, which preceded a delay phase where the memorized images disappeared to cause participants to retain the stimuli until the task's next phase. Following the delay, participants concluded the task by responding to a two-alternative forced choice (2AFC) task, where they identified retained stimuli against foil distractors. These images resembled the memorized samples. We measured response accuracy and speed and compared scores between visual and visuohaptic sensory modality conditions.

Our findings demonstrate that visuohaptic encoding significantly decreases error rates and response times when encoding tomographic slices. Our observation extends previous findings by demonstrating the applicability of visuohaptic integration retention enhancements to a real-world use case. Our research results are valuable in conceptualizing scientific visualization systems that can leverage users' inherent multisensory integration abilities for the optimal encoding of tomographic data. For morphologists, integrating haptics in data visualization platforms might enhance their ability to retain accurate mental representations of fossil images and consequently improve their performance in tasks where precise memory of spatial relationships is crucial.

2 Related Work

2.1 Digital Morphology Challenges

Current digital morphology methods draw on tools designed for importing, visualizing, processing, segmenting, and quantifying tomographic image datasets of specimens [Maga 2023]. For example, to prepare tomographic data for quantitative analyses, morphologists leverage image processing tools such as Fiji [Schindelin et al. 2012] and ImageJ [Abràmoff et al. 2004]. On the other hand, platforms like MorphoJ [Klingenberg 2011] provide an integrated environment where practitioners can conduct various geometric morphometric analyses of tomographic volumes and their 2D slices alike. Comprehensive general-use platforms, such as Amira [Stalling et al. 2005] and 3D Slicer [Pieper et al. 2004], support visualization, segmentation, and quantification of specimens and facilitate statistical and comparative studies. As these general-purpose visualization tools were not specifically designed to address the unique challenges morphologists face, researchers have extended these platforms to suit their needs better. For example, SlicerMorph enhances the 3D Slicer platform to accommodate specific morphological analysis requirements, including retrieving, visualizing, measuring, and annotating digital specimens [Rolfe et al. 2021]. However, although the advent of particular solutions has addressed or alleviated some of the challenges in the digital morphology workflow, current tools still fail to provide morphologists with intuitive and efficient means to perform digital fossil preparation, which remains a burdensome and cognitively demanding endeavor [Sutton et al. 2016]. The integration of Virtual Reality (VR) into scientific visualization platforms [Pinter et al. 2020; Rodrigues et al. 2023; Shetty et al. 2011] represents an essential advancement in improving the interaction with tomographic data, as VR provides enhanced spatial and depth cues that might potentially aid morphologists in visualizing and understanding complex 3D structures [Bryson 1996; Pausch et al. 1997]. However, while these immersive solutions might improve certain aspects of the digital morphology workflow, their current interactive capabilities fall short of improving digital preparation as they are limited to passive viewing rather than active manipulation or segmentation of data [Bimber et al. 2002; Eckhoff et al. 2003]. More specifically, current tools still fall short in supporting cognitively demanding tasks requiring morphologists to mentally represent and accurately interpret the internal spatial features of 3D structures based on their 2D cross-sections to make informed decisions as they work across tomographic slices [Pandolfi et al. 2020; Ziegler et al. 2010]. Currently, the tools employed in digital morphology's manual processing tasks do not fully support the memory retention demands of their workflows [Siqueira Rodrigues et al. 2023; Sutton et al. 2016].

2.2 Visuohaptic Integration in Visualization

Researchers have been investigating the effects of integrating haptics into visualizations since the introduction of haptic displays [Massie and Salisbury 1994] and methods that communicate tomographic volume data as force-feedback [Iwata and Noma 1993; Rodrigues et al. 2024]. Haptic rendering algorithms such as the finger-proxy and god-object methods [Ruspini et al. 1997; Zilles and Salisbury 1995] tackled initial technical challenges and were posteriorly integrated into open-source frameworks such as Chai3D [F. Conti et al. 2003] and H3D [Panëels et al. 2013] to enable researchers to create customized haptic visualization solutions. Researchers demonstrated several benefits of coupling vision and haptics in visualization, as haptic hardware and rendering methods advanced. For example, Lawrence et al. reported on the improvements brought about by haptics in communicating the properties of the different types of data fields [Lawrence et al. 2004]. Anderlind et al. established that haptics accelerates the outlining of target areas in medical imaging segmentation [Anderlind et al. 2008]. Palmerius et al. demonstrated that force-feedback enables users to detect fuzzy data structures during volume rendering exploration [Palmerius and Forsell 2009]. Mendez et al. showed that haptics improve different aspects of volume data navigation [Mendez et al. 2005]. Additional benefits include enhanced path following [Faludi et al. 2019] and target selection [Wall and Harwin 2000]. Although integrating haptics in visualizations has been shown to improve learning [Bara et al. 2007; Bivall et al. 2011], knowledge of its effects on the retention of tomographic images remains limited.

2.3 Behavioral and Theoretical Basis for Haptics to Enhance Memory Retention

The literature in experimental psychology and cognitive neuroscience indicates that the coherent integration of haptic and visual signals may enhance sensory encoding and facilitate stimulus retention in working memory. Since the early behavioral investigations of Loomis [Loomis 1982] and Klatzky [Klatzky et al. 1985], researchers have been exploring whether haptic and visual sensory information share mental representations that can be encoded and retrieved by both senses [Grunwald 2008]. In addition to behavioral evidence, neuroimaging studies have demonstrated that visual and haptic stimulation activate coinciding cerebral areas that encode and host modality-independent and abstract object representations [Amedi et al. 2001; James et al. 2002]. Cross-modal priming further supports the existence of shared mental representations, as object characteristics encoded through vision can be retrieved via touch, and vice versa, and are similar to within-modal priming [Easton et al. 1997a,b; Reales and Ballesteros 1999]. Additional behavioral evidence of such shared representations is provided by the strikingly comparable patterns that vision and haptics display in shape perception and object identification [Craddock and Lawson 2009; Gaissert and Wallraven 2012]. Therefore, as the literature provides extensive evidence of the natural cognitive synergy between vision and haptics, the congruent integration of these senses is likely to reap perceptual enhancements that might ultimately enhance the robustness of resulting mental representations and create behavioral benefits [Lalanne and Lorenceau 2004].

2.4 Demonstrated Effects of Visuohaptic Integration on Memory Retention

Previous research has examined the memory retention effects of integrating vision and haptics during stimulus encoding. For instance, Jones et al. reported that visuohaptic integration increased accuracy in an identification task involving unfamiliar objects [Jones et al. 2005]. Also, Seaborn et al. utilized a pattern-matching task to compare the effects of encoding modalities on memory and workload, finding that the integration of visual and vibrotactile cues improves stimulus retention without impacting cognitive load [Seaborn et al. 2010]. In a study comparing visual and visuohaptic exploration of physical objects, Kalenine et al. observed that bimodal encoding was superior to its vision-only counterpart [Kalenine et al. 2011]. Accordingly, Wijntjes et al. compared the perception of object shapes in vision-only and visuohaptic conditions. They reported that the integration of haptics improves accuracy due to its ability to disambiguate visual distortions [Wijntjes et al. 2009]. Additionally, Jüttner et al. demonstrated that preconditioning visuohaptic exploration outperformed its unimodal visual and haptic counterparts in influencing retention efficacy efficiency at a posterior learning task [Juttner et al. 2001]. Although Kreimeier et al. reported that including vibrotactile feedback increased shape identification accuracy, these researchers associated these haptic cues with slower response times [Kreimeier et al. 2019]. Comparably, Siqueira Rodrigues et al. reported that their visuohaptic encoding of digital objects yielded lower error rates but did not significantly affect response times in comparison to their vision-only encoding condition [Siqueira Rodrigues et al. 2024a]. However, in a later study using a 2D display environment, the same authors reported lower response times in the visuohaptic condition [Siqueira Rodrigues et al. 2024b]. Similarly to error rates, response times are generally expected to be indicators of mental representation robustness, as more reliable memories can be retrieved more rapidly [Miner and Reder 1994] as behavioral benefits of early multisensory facilitation [Smith and Gasser 2005; Stein and Meredith 1993]. While most previous studies have established that visuohaptic integration yields memory retention benefits, there is limited knowledge on whether these findings would apply to use case data such as the tomographic images processed in the morphology workflow.

3 Methodology

In a within-subject study, we applied a DMTS task with visual and visuohaptic encoding modality conditions. The graphical presentation was delivered through a desktop screen, whereas a grounded force-feedback device provided haptic rendering. We measured error rate and response time to assess whether the supplementation of haptic feedback could result in performance enhancements. Based on related literature, we hypothesized the following:

- **H1:** Visuohaptic encoding will lower error rates than the visual encoding modality condition.
- **H2:** Visuohaptic encoding will result in shorter response times than the visual encoding modality condition.

Figure 2: A participant interacts with a stimulus using a desktop display and a force-feedback device during a trial.

3.1 Experimental Design Pre-study

We conducted a pre-study to explore the feasibility of our task design and validate our stimuli set before implementing the main experiment. This study enabled us to identify and address experimental design and technical shortcomings and ensure that the chosen stimuli and tasks were suitable for the intended memory retention evaluations. In this pre-study, four participants completed a total of 240 trials. The quantitative results and qualitative feedback collected during this preliminary study allowed us to make key adjustments to our experimental design. First, we fine-tuned the visual presentation of stimuli to ensure consistency and clarity across trials. Additionally, certain task parameters, such as the time limits for learning and testing phases, were exploratively adjusted to better align with the cognitive load expected in the main study. The pre-study included a haptic-only condition where participants experienced haptic cues solely at touched locations without accompanying visual cues. This condition aimed to evaluate whether participants could effectively encode and retain the characteristics of tomographic images based purely on haptic feedback, which had been deemed possible in previous research using synthesized stimuli created on 5×5 matrices [Siqueira Rodrigues et al. 2024a,b].

In contrast, our results indicated that the haptic-only condition was not feasible within our experimental framework as its error rates averaged above chance ($\bar{x} = 0.64$, $\sigma = 0.48$), strikingly higher than its visual ($\bar{x} = 0.36$, $\sigma = 0.48$) and visuohaptic ($\bar{x} = 0.31$, $\sigma = 0.47$) counterparts. This finding aligns with existing literature on haptic perception and memory, which consistently reports that sighted individuals tend to perform poorly when sightlessly exploring two-dimensional haptic images, even when these images are familiar or represent simple objects [Fradin et al. 2023; Lederman et al. 1990; Schiff and Foulke 1982]. Given that tomographic slices are considerably more complex and that the nature of this task paradigm required us to select image excerpts devoid of semantic meaning, we anticipated that our stimuli would be challenging to memorize within the constraints of a brief learning phase in a DMTS. Thus, the haptic-only condition performance led to its exclusion from the main study, allowing us to focus on the visual and visuohaptic conditions, which were more likely to yield meaningful data and contribute to a better understanding of the effects of multisensory integration on memory retention in a professional use case setting.

3.2 Participants

Participants possessed corrected-to-normal or normal vision, were reportedly right-handed, and free of neurological or psychiatric disorders. Individuals reported that they did not have previous experience with force-feedback haptic devices. Participants knew the research project's goals but did not know the research hypotheses to avoid biases for and against the research outcomes. They were recruited through online advertisement, provided written informed consent upon arrival, and were monetarily compensated with 30 Euros upon study completion. 18 individuals completed the study (N=18, age: 27.5 ± 3.79, 10 females, 8 males). A participant is shown in Figure 2.

3.3 Procedure

Participants began the study by providing demographic data and written informed consent. They were then introduced to the experimental setup and accommodated around the apparatus, which included height adjustments to the elbow support and alignment of the haptic device to their right shoulders, ensuring similar elbow pivoting ranges across all participants. Participants then completed three untimed guided training trials for each condition. Next, timed training continued until participants felt sufficiently prepared for the task. Participants completed 96 trials, organized into four experimental runs of 24 trials each, each taking approximately 15 minutes. Each run consisted of two trial blocks of 12 trials, corresponding to the two encoding modality conditions and counterbalanced. Each experimental run was followed by participant-chosen breaks, which generally lasted between one and five minutes. The haptic device was recalibrated between experimental runs to ensure consistency between virtual and physical probe positions and enable congruent haptic feedback.

3.4 Apparatus

For haptics, we employed a 3D Systems Touch grounded force-feedback device (3D Systems, Rock Hill, SC, United States). The application presented the stimuli using an XP-Pen 22E Display (XPPEN Technology Co, Shenzhen, China), chosen solely for its adjustable horizontal support, as its touchscreen capabilities were not utilized. We employed a LogiLink Numerical Keypad (LogiLink GmbH, Schalksmühle, Germany) for participant answer input in the 2AFC task. The hardware setup included a desktop computer capable of rendering graphics at 60Hz and haptics at 1000 Hz. The experimental application was developed using Visual Studio 2022 and the Chai3D Framework [F. Conti et al. 2003] on Windows 10.

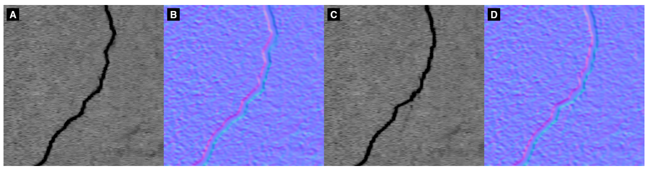

Figure 3: Sample stimulus (A) and its normal map (B). Foil Stimulus (C) and its normal map (D). Stimuli have a resolution of 512×512 and are excerpts from a fossil scan dataset. Foils differ from samples by minor changes to their visual landmarks. Trials presented unique samples and foil pairs.

3.5 Stimuli

We developed a distinct stimulus for each trial, and this image set was displayed to participants in a randomized order. Stimuli consisted of cropped sections from 2D tomographic slices stemming from Computer Tomography (CT) scans of fossil specimens. Image sections were selected to align with the time constraints of the DMTS task, which required stimuli to be sufficiently simple to enable memorization within the DMTS learning phase. As studies employing this task require numerous repeated measures to attribute observed effects to controlled variables confidently, visually complex image sections or three-dimensional volume rendering could not be utilized as stimuli. Selected image excerpts were intentionally abstracted to prevent semantic processing and minimize long-term memory effects associated with participants' prior knowledge of fossil morphology. Selected stimuli magnification rates aimed to resemble the views that morphologists typically observe when making precise selections during image segmentation, which is also the case when examining physical specimens through microscopes. Figure 3(A) shows an example of a sample stimulus. Entropy and edge detection scores were utilized to maintain visual complexity consistency among stimuli and control for performance discrepancies. To ensure that each stimulus equally impacted encoding conditions, stimuli were alternated between conditions and presented to an even number of participants. Each sample was paired with a foil stimulus, generated through parameterized algorithmic transformations involving slight adjustments to landmark points, as shown in Figure 3(C). As evident and detectable foil stimuli transformations would undermine the task's objectives, we manually reviewed foil samples and alternated half of the samples with their corresponding foils. To render stimuli to haptic perception, we generated normal maps for each stimulus, translating grayscale differences as topological depth variations. As illustrated in Figure 3(B), we applied Gaussian blur and thresholding during normal map generation to selectively render texture details to prevent occasional haptic rendering malfunctions caused by brighter and sharper regions [1]. Foils were also paired with normal maps generated under the same conditions as those used for the original stimuli, as demonstrated in Figure 3(D). The generated normal maps encoded micro-geometry information representing the direction vectors at each pixel and were rendered haptically as textures and topographies. Using Chai3D's collision and force-rendering algorithms [F. Conti et al. 2003], contact points between the virtual representation of the haptic stylus and stimulus surfaces were used to sample normal vectors and determine the direction and strength of force-feedback during trials. Although we did not modify the original force-rendering algorithms, material stiffness was capped at 70% of our haptic device's capacity to prevent undesirable artifacts and eventual loss of movement agency. Haptic rendering and normal map generation settings can be obtained in the repository included in section 7.

Our study employed a *DMTS task*, a cognitive evaluation tool that presents a sample stimulus for memory encoding, followed by a delay where the stimulus is absent, which requires participants to retain its mental representation [Daniel et al. 2016; Miller et al. 1968]. After the delay phase, participants completed a *2AFC* task, identifying the retained stimulus next to a similar distractor stimulus, or foil [Bogacz et al. 2006]. During the encoding phase, a sample stimulus of either visual or visuohaptic condition was presented at the center of the workspace for twelve seconds. Following a five-second delay, participants had up to 24 seconds to compare and choose between sample and foil stimuli and identify which matched the original stimulus. In this 2AFC task, participants used left and right arrow keys in a Numpad keyboard to indicate the target stimulus' position. We randomized and balanced target positions across trials to prevent response biases. Participants received visual feedback indicating whether their choices were correct (i.e., a green "+" sign or a red "x" character). Trials were separated by five-second intervals that elapsed once participants indicated their responses. Before a new trial commenced, participants were nudged to raise the haptic stylus above the stimulus cover mask.

A mask overlay covered stimuli in the learning and testing phases and in both encoding modality conditions. Participants used the haptic probe to reveal the stimuli's appearance through a circular aperture at the point of contact, as depicted in Figure 4. Our design was inspired by Loomis et al. [Loomis et al. 1991] and Jones et al. [Jones et al. 2005], both of whom used a similar sampling restriction strategy to make encoding modality conditions comparable. As haptic encoding is generally performed through successive impressions [Gibson 1962] and vision is capable of simultaneously sampling multiple areas [Lederman et al. 1990], humans rely typically on and prioritize vision for perceiving geometric features [Zangaladze et al. 1999]. Thus, restricting visual presentation to touched areas ensured that participants would perform similar movements in both encoding conditions and be exposed to potential haptic cues while examining stimuli. In the visual encoding condition, participants revealed the stimulus at probe positions, whereas, in the visuohaptic condition, they could explore stimuli using both touch and vision.

[1] Nvidia Texture Tools settings: BC4u grayscale format, Object space normal map image, Box filter for mipmaps, Max RGB height source, height generation using dUdV normal filter with Min Z = 0.674, Scale = 64, and Alpha Field set to Height (Normalized). Applied filters included Negative, Darker, Smooth, and Gaussian Blur with a radius 9. The DPF preset containing these settings is included in our open-source repository.

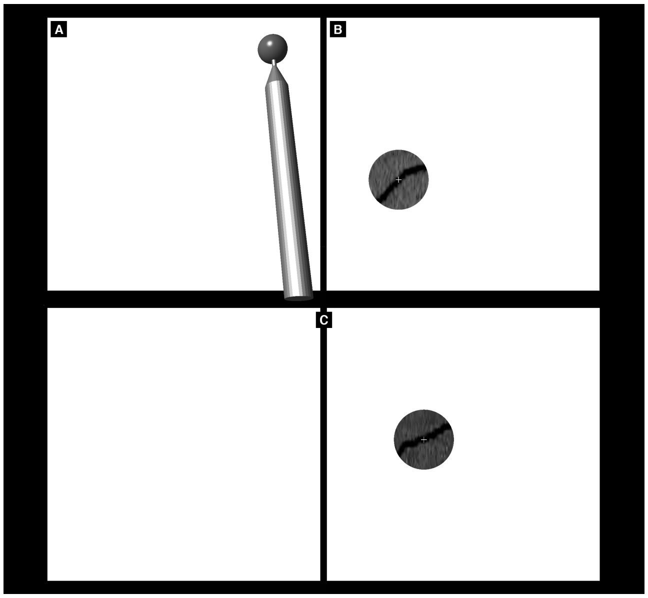

Figure 4: (A) The haptic probe approaches the masked stimulus. (B) Learning phase: A circular aperture reveals the stimulus at the touched point. (C) Testing Phase: Examination of sample and foil stimuli, presented side-by-side.

While this task design prioritizes experimental control, ecological validity is also considered. Morphology workflows often involve interaction with magnified areas of tomographic slices during the selection of regions of interest for semi-automatic image segmentation of specimens [Pandolfi et al. 2020; Sutton et al. 2016]. Although scientific visualization software does not mask the remaining parts of working images as in our circular aperture design, users arguably focus their visual attention on limited radii surrounding their selection cursors. While morphologists currently perform selections through mouse or stylus devices and not through a haptic device, their workflow's sequential interaction with limited parts of tomographic slices connects with our proposed design. The connection between our DMTS task and the cognitive demands of the image segmentation task and associated cross-sectioning in morphology is discussed in 5.3.

3.6 Independent Variables

We defined Encoding Modality as an independent variable encompassing *Visual* and *Visuohaptic* conditions. In *Visual* condition trials, participants explored sample stimuli only visually as its haptic feedback was limited to conveying that the probe was in contact with the stimulus, not providing haptic cues of stimulus characteristics. In contrast, in the *Visuohaptic* condition, stimulus characteristics were presented through visual and haptic rendering.

3.7 Dependent Variables

This study included *Error Rate* and *Response Time* as dependent variables. *Error Rate* represents the relative number of erroneous 2AFC responses, which occurred when participants opted for a foil rather than the encoded target stimulus. *Response Time* was measured as the interval between the testing phase's beginning (i.e., the first appearance of target and foil stimuli) and response execution (i.e., the pressing of an arrow key).

4 Results

Eighteen participants completed the experiment and reached overall performance above 60% (58 or more correct responses in 96 trials), the minimum score required to perform significantly above chance at $p < .05$ according to a binomial distribution. We statistically examined error rate and response time for significant differences between encoding modality conditions. We applied a Shapiro-Wilk test to investigate data distribution and applied appropriate statistical testing to determine statistical differences between measures. Cohen's d was reported as an effect size measure.

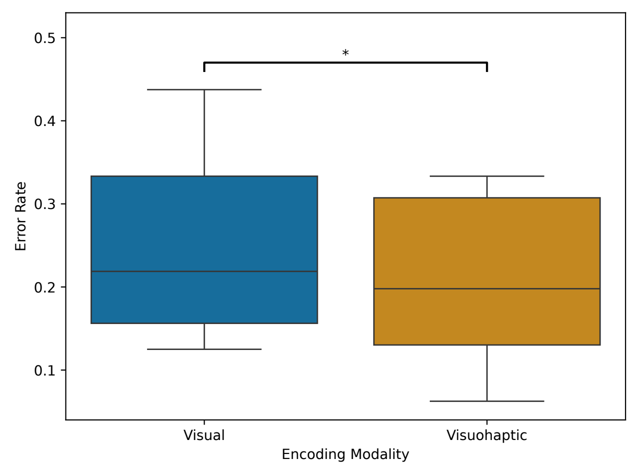

Figure 5: Error rates across conditions. Asterisks indicate significant differences between conditions, as determined by paired-sample t-tests. We find significant differences between visual and visuohaptic conditions, with trials in the visuohaptic condition resulting in lower error rates.

4.1 Error Rate

As determined by a Shapiro-Wilk test, error rates followed a normal distribution ($p > .05$). Thus, a paired-sample t-test reported a significant difference in error rates between the visual and visuohaptic encoding modality conditions, $t(17) = 4.92, p < .001, d = 0.48$. The visuohaptic condition resulted in a lower error rate ($\bar{x} = 0.20$, $\sigma = 0.10$) compared to the visual condition ($\bar{x} = 0.25$, $\sigma = 0.10$). The mean error rate per participant is depicted in Figure 5.

4.2 Response Time

A Shapiro-Wilk test determined that response times adhered to a normal distribution ($p > .05$). Accordingly, a paired-sample t-test revealed a significant difference in response times between visual and visuohaptic conditions, $t(17) = 2.31, p = .034, d = 0.13$. The visuohaptic encoding condition produced shorter response times ($\bar{x} = 13.40$, $\sigma = 4.07$) compared to the visual condition ($\bar{x} = 13.94$, $\sigma = 4.20$) as illustrated in Figure 6.

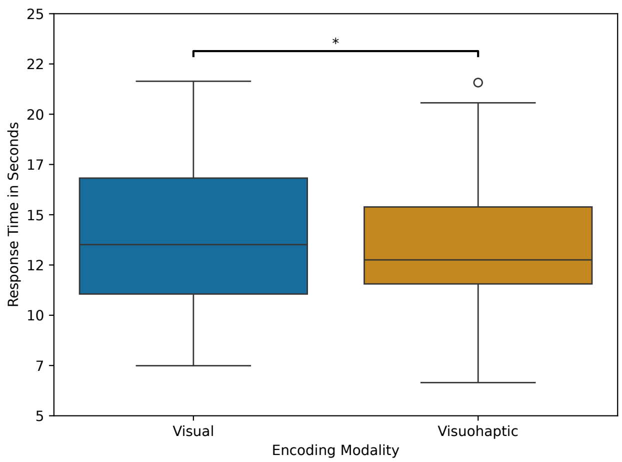

Figure 6: Response times across conditions. Asterisks indicate significant differences between conditions, as determined by paired-sample t-tests. We find significant differences between visual and visuohaptic modalities, with visuohaptic encoding resulting in shorter response times.

5 Discussion

5.1 Visuohaptic Encoding Modality Results in Lower Error Rates

Our results indicate that the visuohaptic encoding modality significantly reduces error rates in comparison with the visual encoding condition, which supports our first hypothesis (H1). In regard to the corresponding analysis reported by Siqueira Rodrigues et al. for these two conditions [Siqueira Rodrigues et al. 2024a], our results reported a slightly larger effect size ($d = 0.48$ vs $d = 0.41$) and greater significance levels ($p < .001$ vs $p = .011$), which might be due to our increased total of trials per condition (864 vs 600). Although there is no evidence that additional encoding time would exclusively benefit the visuohaptic condition, it is important to note that our study provided longer encoding time (12 vs 7 seconds) to both conditions, as our pilot results evidenced as necessary for task completion due to the higher complexity of our stimuli. Another important factor that might impact this analysis is the difference in display environment, as the aforementioned experiment employed an immersive environment whereas our study utilized a desktop display. Although our experiments' stimuli appear to be more complex than their corresponding counterparts in the cited study, mean error rates were similar for the visuohaptic ($\bar{x} = 0.20$ vs $\bar{x} = 0.19$) and visual ($\bar{x} = 0.25$ vs $\bar{x} = 0.24$) conditions, which could result from the interplay between stimulus complexity, encoding time, and display environment, as VR might potentially have a detrimental effect on memory performance [Juliano et al. 2022; Kargut et al. 2024]. In addition to their similarity to the above study, our findings generally align with previous research that has shown the benefits of integrating sensory information from multiple sensory modalities to form more accurate mental representations [Engelkamp and Zimmer 1994; Loomis 1982]. In the context of our study, the combination of visual and haptic feedback likely provided complementary cues that enhanced participants' ability to encode and recall the details of tomographic slices more accurately than using solely visual cues [Gaissert and Wallraven 2012; Klatzky et al. 1985]. This multisensory integration may offer a richer set of retrieval cues, leading to more robust mental representations compared to when using visual input alone [Engelkamp 1995]. These findings are consistent with studies that have observed enhanced accuracy through multimodal encoding strategies, even though the specific contexts and modalities differ [Juttner et al. 2001; Kreimeier et al. 2019; Seaborn et al. 2010].

5.2 Visuohaptic Encoding Modality Results in Shorter Response Times

Our results indicate that visuohaptic encoding significantly reduces response times in comparison with the visual condition, which supports the hypothesis (H2). Our findings contrast with results reported by Siqueira Rodrigues et al., who did not find a significant effect of visuohaptic integration on response times [Siqueira Rodrigues et al. 2024a]. Several factors might account for this divergence, such as differences in statistical tests, number of trials per condition, testing time limits, and display environment. In the data analyzed by these previous authors, response times were not normally distributed, which caused them to utilize the Friedman test and Bonferroni-corrected Wilcoxon-signed rank post hoc tests as opposed to the paired-samples t-test we could employ to analyze our normally-distributed data. Although the effect size was small in both studies ($d = 0.13$ vs $d = 0.04$), our increased total of trials per condition (864 vs 600) might also have contributed to this difference in significance levels. Additionally, our experimental design allowed for longer exploration in the testing phase (up to 24 vs 14 seconds), potentially increasing the average response times across visuohaptic ($\bar{x} = 13.40$ vs $\bar{x} = 9.39$) and visual ($\bar{x} = 13.94$ vs $\bar{x} = 9.50$), which is to be expected as participants are generally predisposed to pace themselves according to the testing phase's available time [Bogacz et al. 2006]. The VR environment showcased by previous authors might also have adversely affected their participants' response times, as VR may increase cognitive load and impact task efficiency, especially among VR novices [Makransky et al. 2019; Sagnier et al. 2020]. In fact, in a similar study employing 2D displays, authors reported shorter response times in the visuohaptic condition, which aligns with our findings [Siqueira Rodrigues et al. 2024b]. Generally, response times are expected to positively correlate with error rates in indicating the robustness of mental representations, as sturdier memory traces can be accessed more efficiently [Miner and Reder 1994]. Coherent multisensory encoding, such as the visuohaptic modality in our study, provides redundant signals and might result in early multisensory facilitation, which may result in behavioral benefits such as enhanced decision-making [Smith and Gasser 2005; Stein and Meredith 1993]. This interplay between efficiency and effectiveness associated with representations is also observable as memory retrieval efficiency is one of the factors influencing participants' meta-judgment of memory accuracy [Costermans et al. 1992].

5.3 Interaction Design Implications for Scientific Visualization

Our findings have implications for improving the design of scientific visualization applications towards supporting users whose tasks require accurate memory retention of information presented on tomographic images. As our results demonstrate that visuohaptic encoding of tomographic slices stemming from fossil datasets reduces error rates and response times in a working memory task, integrating haptic feedback into scientific visualizations could improve users' ability to retain such data in everyday tasks. Such an improvement could be especially beneficial for morphology professionals, as their workflows involve maintenance and cognitive manipulation of mental representations of image datasets [Meier et al. 2001; Siqueira Rodrigues et al. 2023]. Morphologists heavily utilize scientific visualization platforms to process digital specimens, and labor-intensive tasks such as manual image segmentation, require researchers to select regions of interest on certain tomographic slices while retaining accurate representations of other slices as memorized from different perspectives [Sanandaji et al. 2023; Ziegler et al. 2010]. Indeed, segmentation and other morphology tasks require significant cross-sectioning, namely the ability to accurately interpret and mentally represent the internal spatial features of 3D structures based on their 2D cross-sections [Carroll 1993]. Therefore, integrating haptic feedback into visualization tools may help morphologists maintain accurate mental representations of complex fossil structures, potentially reducing errors and improving decision-making efficiency in their workflows. Compared to previous research that explored the utility of visuohaptic integration on the retention of synthesized stimuli [Siqueira Rodrigues et al. 2024a,b], our findings extend the generalizability of such findings to a professional use case and its corresponding data. As our selection of image sections was limited by the complexity and abstraction constraints of the DMTS task, further investigation using different tasks would be necessary to more thoroughly establish the utility of haptic integration in this context. Our investigation was limited to the interaction with tomographic slices as the most common design space in the morphologist workflow. However, as these professionals also visualize specimens through volume rendering [Sutton et al. 2016], further studies addressing three-dimensional design spaces in visualization would paint a more complete picture of the utility of haptics in the scientific visualization context.

5.4 Limitations and Future Work

Our study's relatively small sample size may limit the generalizability of its findings. Although a sample size of eighteen participants falls within the common range in HCI studies [Caine 2016], future research with more extensive and diverse participant pools would extend the applicability of our reported effects and expand on the robustness of our results. Other factors, such as our choice of haptic feedback device, haptic rendering method, and stimulus design also limit the generalizability of our results. Although grounded force-feedback devices are commonly employed in similar behavioral studies for reliably rendering stimuli [McCormack et al. 2018], our findings may not extrapolate to vibrotactile, exoskeleton, and midair haptic displays, among others. It is also noteworthy that the researchers unavoidably made arbitrary choices regarding the modeling of visual stimulus characteristics into haptic rendering. Leveraging normal maps to communicate grayscale values as topography is just one of the many ways tomographic slices can be rendered haptically, implying that the effects we report might not be observed using other haptic modalities. Our stimulus choices were also limited by their suitability to the DMTS and 2AFC paradigms and the study time limitations. Therefore, although our results indicate that stimulus design was appropriate for our experimental tasks, our findings may not be transferable to tomographic images featuring remarkably different characteristics regarding complexity, salience, contrast, etc. The choice for the DMTS task also has its limitations, as this task is designed to measure stimuli retention only in working memory. While our findings regarding the retention effects of visuohaptic integration apply to common tasks performed within scientific visualization platforms, our results cannot be extrapolated to tasks involving long-term memory. Future research would require a different paradigm to test the utility of haptics in common morphology workflow scenarios involving long-term memory retention, such as visualizing a specimen in preparation for offline physical processing. Since memory retention and mental workload are interconnected [Kosch et al. 2023], measuring mental workload could provide more insights regarding the memorization performance for different haptic rendering modalities.

6 Conclusion

Our study demonstrates that visuohaptic integration significantly enhances memory retention of morphological tomographic images, as evidenced by lower error rates and faster response times in a delayed match-to-sample task. These findings expand the existing knowledge on the utility of sensory integration, validating its application towards complex use case data. Our insights are relevant to morphology workflows, where maintaining accurate memory representations of spatial relationships is important. These results have implications for the design of scientific visualization tools, as incorporating haptic feedback into manual processes such as cross-sectioning and image segmentation may optimize memory retention and consequently improve decision-making processes for morphology professionals. Interface designers might leverage visuohaptic integration to improve workflow efficiency in tasks requiring detailed mental representations of tomographic data, thereby supporting more accurate and efficient analysis and interpretation of complex morphological structures within virtual environments.

7 Data Availability

The data that support the findings of this experiment, along with their corresponding data analysis scripts and software on GitHub[2].

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[2] https://github.com/lsrodri/VHMatchMorph

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