Embodied Spatial Thinking in Tangible Computing

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ABSTRACT
Tangible user interfaces are based on the premise that embodied cognition in computing can enhance cognitive processes. However, the ways in which embodied cognition in computing transform spatial thinking have not yet been rigorously studied. I have co-designed Tangible Landscape – a continuous shape display powered by a geographic information system – and used it to explore how technology mediates spatial cognition in a rigorous experiment.

In this terrain modeling experiment I use geospatial analytics to analyze how visual computing with a GUI and tangible computing with a shape display mediate multidimensional spatial performance.

My initial findings suggest that: **1.** digital sculpting via a GUI is unintuitive, **2.** shape displays like Tangible Landscape can be intuitive, enhance spatial performance, and enable rapid iteration and ideation, and **3.** different analytics encourage significantly different modes of spatial thinking and strategies for modeling.

ACM Classification Keywords
H.5.2. Information Interfaces and Presentation (e.g. HCI): User Interfaces – Evaluation/methodology; Interaction styles; Prototyping; Theory and methods

Author Keywords
Human-computer interaction; tangible user interfaces; tangible interaction; embodied cognition; spatial thinking; 3D modeling

INTRODUCTION
In embodied cognition the mind is embedded in the body. Higher cognitive processes rely on lower level processes such as emotion and sensorimotor processes that link perception and action [2]. Thus body and action mediate thought. Cognitive processes can be physically simulated with cognition offloaded onto action. Objects such as tools can be cognitively grasped and temporarily, contingently incorporated into ones body schema [5]. This view of cognition considers feeling, action, and perception to be functionally integral to thought.

Based on the theory of embodied cognition researchers have theorized a physical-digital divide in human-computer interaction – positing that the high level of abstraction required to interact with a computer via a graphical user interface (GUI) in a visual computing paradigm constrains how we think – and designed innovative technologies for bridging this divide such as tangible user interfaces (TUIs) [3, 1]. TUIs are designed to physically manifest digital data as tangible bits that afford the ability to directly, physically feel and manipulate data [3]. TUIs make pragmatic representations of digital data. Pragmatic representations are conceptual models for rapidly generating action that are primarily based on tactile feedback and are processed automatically, immediately, and subconsciously [4]. By physically manifesting data so that we can pragmatically interact with computations, TUIs should enable rapid, intuitive action and expression in a way that was not possible in visual computing. By enabling embodied cognition in human-computer interaction TUIs should let us cognitively grip data as an extension of our bodies, intuitively manipulate data, and physically simulate processes. This should enhance spatial thinking.

Research on TUIs has been more focused on the design and development of the technology than empirically testing the use and effects of the technology. Rasmussen et al. for example discuss the focus on the design and development of shape displays rather than empirical research about their use. [7]. Research on tangible interaction has focused on user experience and to a lesser degree user performance using methods such as participant observation, semi-structured interviews, video analysis, and small-scale experiments.

While the theory of embodied cognition has inspired the design of novel technologies for human-computer interaction, its applied principles need to be empirically tested, critiqued, and refined in order to improve interaction design. The aim of this research is to study how tangible computing mediates spatial thinking in order to improve interaction design, enhance spatial performance, and improve spatial education.

Testable hypotheses
I hypothesize that:

1. limited feedback constrains spatial performance,
2. misinterpretations of 3D space in visual computing reduce spatial performance,

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3. computational analytics like differencing and flow simulations can enhance spatial performance,
4. computationally enriched analytical thinking can be coordinated with embodied thinking,
5. tangible computing that computationally enhances embodied spatial thinking can improve spatial performance, and
6. tangible computing can enable a rapid iterative process of exploratory, generative form-finding that can improve spatial performance.

METHDOLOGY

I have conducted a rigorous experiment using geospatial analytics to compare spatial performance in analog modeling by hand, in tangible computing using Tangible Landscape, and in visual computing using 3D modeling programs via a GUI. Tangible Landscape is a continuous shape display tightly integrated with GRASS GIS that was designed to intuitively 3D sketch landscapes (Figure 1). Conceptually, Tangible Landscape couples a physical model with a digital model in a real-time feedback cycle of 3D scanning, geospatial modeling and simulation, and projection (Figure 1a) [6].

I have begun to test my hypotheses using quantitative methods Rather than studying basic spatial cognitive abilities that can not usefully be disentangled in applied use, I am studying applied spatial cognitive processes using the metrics and parameters of the given application. I am studying how participants perform in a series of time constrained terrain modeling exercises using analog modeling, visual computing, and tangible computing. 6 landscape architects and 6 geospatial analysts have participated in this pilot study. I am assessing their performance with each technology using spatial statistics, topographic parameters, morphology, process-form interactions, and differencing.

Terrain modeling experiment

The 1st exercise tests spatial performance in analog modeling to establish the baseline spatial ability of each participant. In this exercise participants sculpt a given terrain in polymeric sand using their hands with a CNC routed model for reference.

The 2nd exercise tests spatial performance in projection augmented analog modeling to establish a baseline for spatial performance in tangible computing. In this exercise participants sculpt a given terrain in polymeric sand using a projected map of the given elevation and contours as a guide.

The 3rd-5th exercises test spatial performance in tangible computing augmented with different analytics. In the 3rd exercise participants use Tangible Landscape to sculpt a given terrain in polymeric sand using the given and scanned contours as a guide. In the 4th exercise participants use Tangible Landscape to sculpt a given terrain in polymeric sand using the difference between the given and the scanned landscape as a guide. In the 5th exercise participants use Tangible Landscape to sculpt a given terrain in polymeric sand using the simulated water flow over the scanned landscape as a guide in order to study 4D thinking.

The 6th and 7th exercises test spatial performance in visual computing. In the 6th exercise participants digitally sculpt a given terrain in Rhinoceros, a 3D modeling program, using the given 3D contours as a guide. In the 7th exercise participants digitally sculpt a given terrain in VUE, a 3D modeling program designed for intuitive terrain sculpting, with a CNC routed model for reference.

Data collection and analysis

In the 1st-5th exercises the resulting physical models are 3D scanned, imported into GRASS GIS as point clouds, and interpolated as DEMs for analysis. In the 6th and 7th exercises the resulting digital models are exported as point clouds, imported into GRASS GIS, and interpolated as DEMs for analysis. For each model I compute the elevation and its histogram and bivariate scatterplot, the slope, the difference and its histogram, the simulated water flow, and morphology. For each exercise I compute a map of the coefficient of variance of all the of DEMs, bivariate scatterplots of the covariance and correlation matrix of all the of DEMs, and the mean and the absolute value of the mean of the differences between the the reference terrain and the modeled terrain.

Code

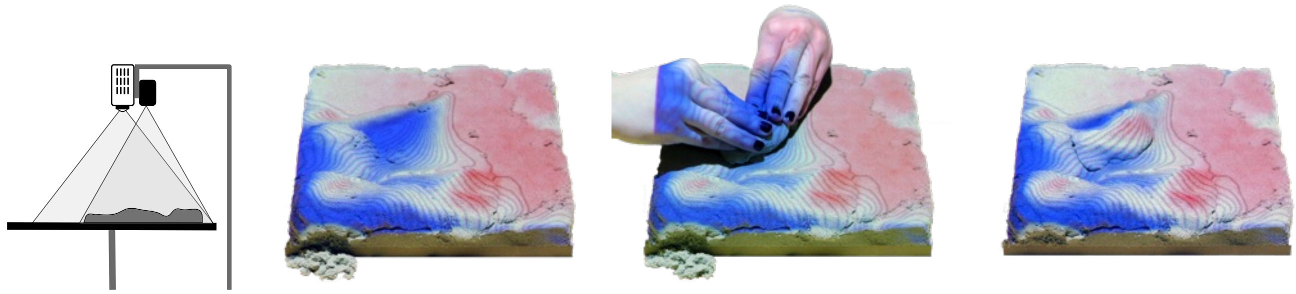
As a work of open science the data and the python scripts for data analysis are publicly available on GitHub at `https://github.com/baharmon/tangible_topography` released under the GNU General Public License version 2. Both GRASS GIS and Tangible Landscape are open source projects released under the GNU General Public License version 2. Tangible Landscape is available on GitHub at `https://github.com/ncsu-osgeorel/grass-tangible-landscape`.

PRELIMINARY RESULTS

Select results for one participant in the pilot study are shown in Figures 3, 4, and 5.

In the 1st exercise participants tended to model the overall form well, but exaggerated the slopes and misplaced the main ridge. In the 2nd exercise participants tended to model the landscape very well, accurately capturing the ridge and valley, but missing the saddle of the valley (Figure 2a). In the 3rd exercise participants tended to model the overall form well, but approximately with indistinct landforms and a lot of roughness. Many participants used a layered *pancake*-modeling strategy here. The 4th exercise tended to have the best results. Participants used a rapid iterative process to accurately model the landscape. In the 5th exercise participants tended to model the overall form well, but exaggerated the slopes of the stream channels. In the 6th exercise most participants modeled the form very poorly especially the interior space (Figure 2b) – either modeling only the edges or modeling very approximate massings of the main ridge and peak. Expert 3D modelers, however, modeled the form better, but still missed much of the interior space. In the 7th exercise participants tended to model the landscape suggestively in the x- and y-dimensions, but underestimated and grossly distorted the z-dimension.

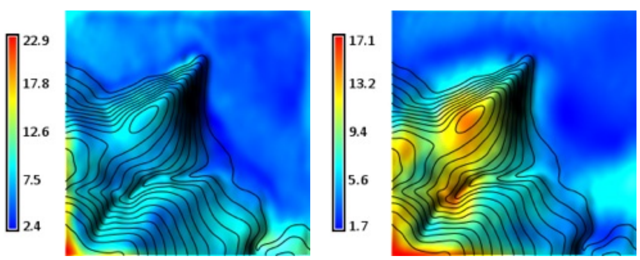
The pilot study suggests that **1.** analog sculpting by hand can be highly intuitive, but the lack of analytical feedback limits



(a) (b) (c) (d)

Figure 1. 3D sketching with Tangible Landscape: (a) a cycle of scanning and projection couples a physical and digital model, (b) the differencing analytic with blue where sand should be added and red where sand should be removed, (c) a participant adding sand, and (d) the updated differencing analytic.

ones ability to critique the model and refine its form, **2.** shape displays like Tangible Landscape can be intuitive, enhance spatial performance, and enable rapid iteration and thus creative spatial learning. **3.** digital sculpting via a graphical user interface is unintuitive and visually ambiguous leading to misinterpretations of depth, height, and interior space.



(a) (b)

Figure 2. Standard deviations of the differences for all participants: (a) in Ex. 2 using projection augmented modeling and (b) in Ex. 6 using Rhinoceros.

FUTURE WORK

The full study will have approximately 40 participants. Based on the results of the study I hope to develop a theory of how technology mediates spatial cognition. In the long-term I plan to expand this study of embodied spatial cognition in tangible computing as a collaborative research project with psychologists using spatial analytics, eye tracking, biometric sensors, and EEGs.

CONCLUSIONS

This study is unique in applying geospatial analyses to asses spatial performance in tangible interaction. My initial findings suggest that shape displays like Tangible Landscape can with the right computational analytics enhance performance in novel ways and enable rapid iterations of generative form-finding and critical analysis. Different analytics encourage significantly different modes of spatial thinking and strategies for modeling. The differencing analytic leads to significant improvements in spatial performance and enables an iterative process.

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My colleagues in the NCSU Open Source Geospatial Research and Education Lab (http://geospatial.ncsu.edu/osgeorel/) Anna Petrasova, Vaclav Petras, Helena Mitasova, and Ross Meentemeyer contributed to this research by collaboratively designing Tangible Landscape and helping to run the experiment.

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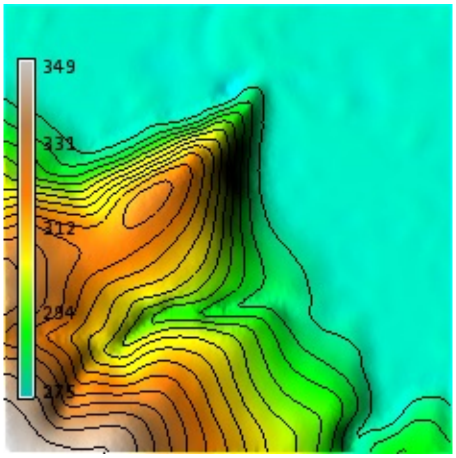
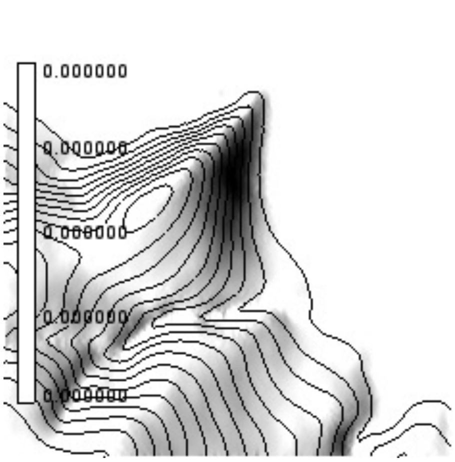


(a)



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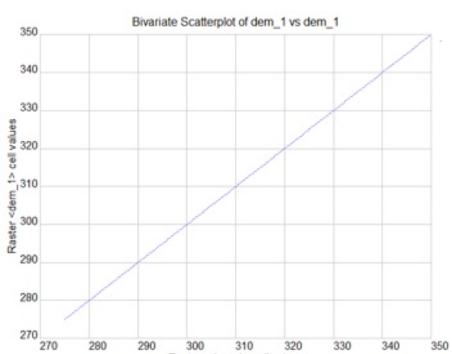
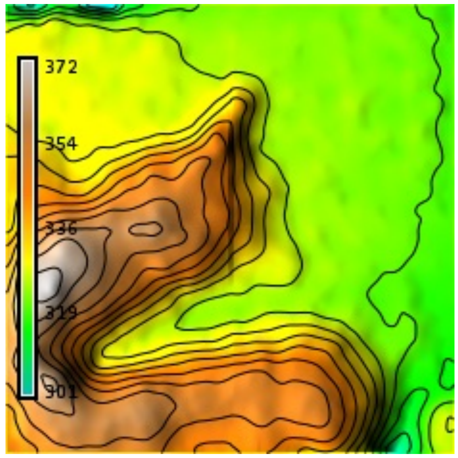


(c)

Figure 3. **Reference model:**
(a) the digital elevation model (DEM),
(b) the difference between the reference DEM and the reference DEM, and
(c) the bivariate scatterplot of the difference between the reference DEM and the reference DEM.



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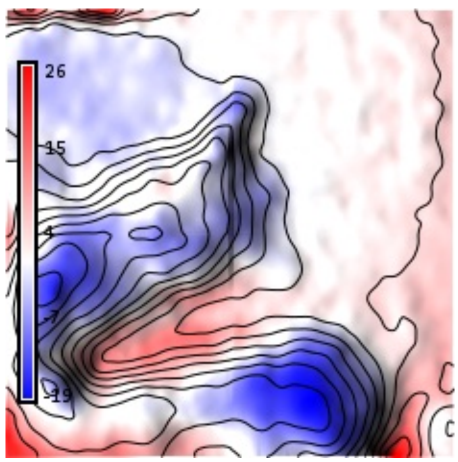

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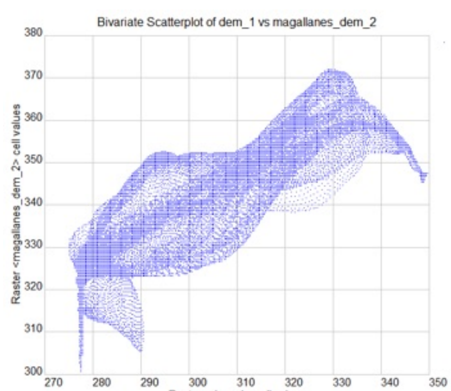
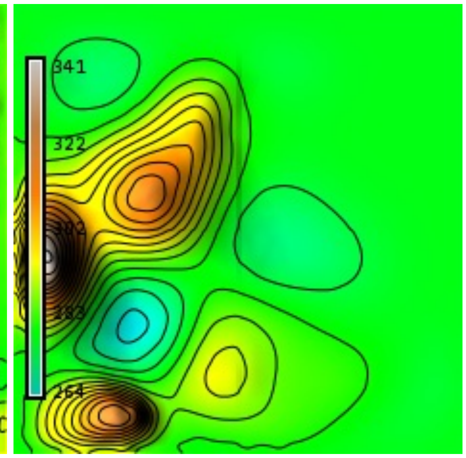


(c)

Figure 4. **Participant's model for Ex. 2 using projection augmented modeling:**
(a) the DEM,
(b) the difference between the participant's DEM and the reference DEM, and
(c) the bivariate scatterplot of the difference between the participant's DEM and the reference DEM.



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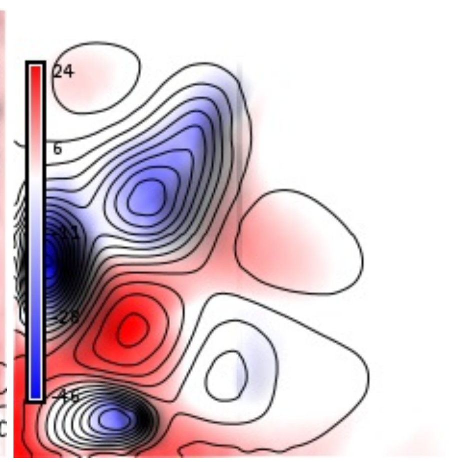

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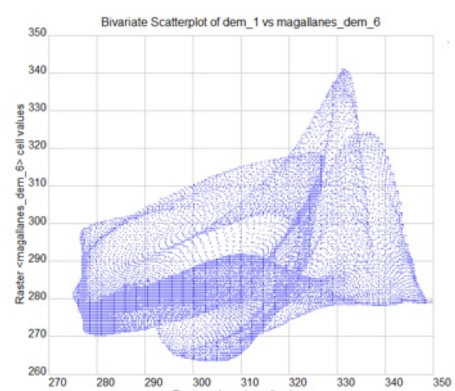

(c)

Figure 5. **Participant's model for Ex. 6 using digital sculpting with Rhinoceros:**
(a) the DEM,
(b) the difference between the participant's DEM and reference DEM, and
(c) the bivariate scatterplot of the difference between the participant's DEM and the reference DEM.