Tangible Meets Gestural: Gesture Based Interaction with Active Tokens

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ABSTRACT

Emerging multi-touch and tangible interaction techniques have a potential for enhancing learning and discovery but have limitations when manipulating large data sets. Our goal is to define novel interaction techniques for multi-touch and tangible interfaces, which support the exploration of and learning from large data sets. In this paper we discuss conceptual, cognitive, and technical dimensions of gestural interaction with active tangible tokens for manipulating large data sets.

Author Keywords

Tangible interaction; active tokens; gesture-based interaction; big data.

ACM Classification Keywords

H.5.2 [Information Interfaces and Presentation]: User Interfaces---*input devices and strategies, interaction styles*.

INTRODUCTION

To date, little research has been devoted to investigating tangible and multi-touch interaction in data-intensive domains such as genomics, environmental studies, and social networks. Here, learning and discovery rely on manipulating large data sets using sophisticated computational methods [25]. Tangible and tabletop interactions provide form factors that foster collaboration through visibility of actions, multiple access points, and egalitarian input [10, 17, 26], and support distributed cognition [22, 26]. In the context of data exploration, the ability to support collaborative work and enhance reasoning could lead to new discoveries.

Designing tangible and multi-touch systems that support learning and discovery in *data-intensive* areas requires going beyond the application of existing interaction techniques. While direct touch is currently a standard input method for interactive surfaces, in data-intense applications visual representations are typically small, finger size and occlusion may interfere with direct interaction of small targets through touch [9, 32]. Similarly, WIMP-style control elements provided by various multi-touch toolkits, such as scrollbars, sliders, check boxes, and text fields, may often pose the same challenges for effective and accurate touch interaction, or take expensive screen real-estate [9]. For some data manipulation tasks that require high precision, touch-based graphical representations such as knobs and sliders are less effective than their physical counterparts [8].

Several researchers have considered novel multi-touch gesture-based interaction techniques for data driven applications; e.g. [9, 12, 32]. However, while providing advantage over touch interaction with WIMP style controls, multi-touch gestures often suffer from low discoverability and lack of persistence [9]. Considering these limitations of multi-touch interaction for Big Data exploration, we suggest that tangible systems with clear feedback and strong constraints provide an alternative approach for exploring Big Data.

Such systems can utilize both soft (graphical) and hard (physical) tokens and constraints to guide users in querying and interpreting large data sets, enabling users to collaboratively engage in problem solving. Technological advances and mass-market offerings such as Sifteo Cubes [1] also open possibilities for the use of *active tokens* [36].

Active tokens are programmable physical objects with integrated display, sensing, or actuation technologies (e.g., [1, 16, 28, 35, 36]). Thus, they can be reconfigured over time, allowing users to dynamically modify their associations with datasets or controls. The use of active tokens expands the design space of token and constraints interaction [24, 27]. Combining interactive multi-touch surfaces with active tokens could facilitate the presentation and manipulation of Big Data while preserving benefits of tangible interaction such as support for two-handed interaction, co-located collaboration, and strong affordances. We focus on a sub-class of active tokens that can be manipulated using gestures independently from global constraints. Gestural interaction with active tokens blurs the boundaries between tangible and gestural interaction, and fits within the area defined as "tangible gesture interaction" [31].

In this paper, we briefly consider the conceptual dimensions for gestural interaction with tangible active tokens, discuss cognitive foundations for gesture-based interaction with active tokens for discovery and learning, and examine recent technical configurations that are relevant to this area.

CONCEPTUAL DIMENSIONS

Tangible Tokens and Constraints (TAC) systems [24, 27] engage the physical expression of digital syntax through configurations of tokens and constraints. For example, token and constraint relations such as presence, position, sequence, proximity, connection, and adjacency are utilized to encode information as well as to communicate to users what kinds of interactions an interface can (and cannot) support. The manipulation of a token in respect to its constraints results in modifying both physical and digital states of the system. Gestural interaction with active tokens expands the design space of TAC interaction, blurring boundaries between tangible and gestural interaction.

Several prior systems have explored gesture-based interaction with active tokens. For example, the Tangible Video Editor [36] employed active tokens to represent video clips. SynFlo [35] utilized active tokens to simulate a biology experiment and evoked gestures such as pouring and shaking. However, aside from the parameter bars of Tangible Query System [28], the Big Data context has yet to be engaged.

In [30] we investigate user-generated gestures for exploring large data sets. Our findings highlight three characteristics of gestural interaction with tokens: space, flow, and cardinality: *Space* describes where an interaction takes place: typically on-surface (integral), on-bezel (proximal), and in-air (distal). The dimension of *flow* is adopted from [34] and may be regarded as having both discrete and continuous dimensions. *Cardinality* indicates the number of hands and tokens involved in a gesture, with atomic, compound, and parallel subelements. These characteristics are elaborated in [30]. However, gesture sets are yet to be evaluated within task and data-driven scenario.

COGNITIVE FOUNDATIONS

The centralist (brain-centric) view of cognition has in recent decades been shifting to what Killeen and Glenberg [13] call an "Exocentric Paradigm." This posits that cognition is a process that involves the brain, the body, and the environment. This paradigm is supported by a wide array of empirical evidence, which falls broadly under terms like "embodied cognition," "situated cognition," and "distributed cognition" [11, 15, 33]. From the perspective of our active token and Big Data discussion, we are especially interested in how evolving notions of cognition can further our understanding of how people's physical actions and interactions with their environment support scientific reasoning; and how this understanding can inform the design of physical and computational tools for discovery and learning.

External representations and scientific reasoning

From early childhood, our interaction with physical objects appears to be closely connected with our learning and thinking processes. For example, researchers have shown that touching physical objects can help young children learn how to count by helping them keep track of their activities, and by allowing them to connect each physical object with a number [2]. Studies with children have also shown a co-development of language and gesture [6] and the origins of gestures appear to be connected to physical actions.

In thinking about complex problems, scientists employ external artifacts (e.g., models, diagrams, instruments) to support their reasoning [20, 21, 23]. A prominent example is the double helix model of DNA built by Watson and Crick, which enabled the two scientists to quickly form and test out hypotheses by manipulating the model's physical structure. Physical models can thus provide an entry point for the cognitive apparatus in the form of both conceptual and material manipulation [5].

Computational systems can also embody knowledge. Typically, visualizations are used to make computational models accessible to human cognitive capabilities. Some visualizations can be interactively explored and filtered in order to find patterns that might enhance understanding. However, the interaction with most visualizations is not closely connected to the underlying model of the studied phenomenon or system. That is, the interactions users have with most interactive visualizations (e.g., using button clicks, menu selections, etc.) are very unlike Watson and Crick's manipulation of the physical DNA model. In the latter case, the actions made with the physical model were tightly coupled with the scientists' emerging conceptual model, which helped to leverage the connection in the brain between motor, perceptual, cognitive processes in the development of insights [7]. We believe that systems that employ active tokens have the potential to leverage gestural interaction/manipulation in order to create a similar connection between the computational model/data and the user's conceptual model in areas of scientific problem solving.

Tokens and gestures for thinking and learning

Martin and Schwartz [18] have investigated how physical actions impact thinking and learning. They provide four ways in which this happens: induction, off-loading, repurposing, and physically distributed learning. Although our focus is not limited to children, we use these categories as a framework for considering how gestural interactions with active tokens might support thinking and learning.

Induction is when people do not have stable ideas, but they are acting in a stable environment that offers clear feedback and strong constraints that can guide interpretation [18]. In this case, physical actions can enable them to query the environment and test their hypotheses. From an interaction perspective, well-designed feedback and constraints could thus allow TAC systems to support testing of hypotheses and problem solving. For example, graphical (soft) or physical (hard) constraints and the shape of tangibles can suggest ways in which tangibles can be placed on an interactive surface or combined together.

Off-loading is when both people's ideas and the environment in which they operate are stable [18]. In this case, people rely on the environment to reduce cognitive load of a task -- often called distributed cognition [11]. From an interaction perspective, physical tokens can support distributed cognition as users spread and group them in different ways [3, 4, 22]. Although it is also possible to spread and group digital artifacts, e.g. via multi-touch interaction, Antle and Wang's comparison of TUI and multi-touch interaction in a puzzle-solving task [4] revealed that the TUI condition supported more efficient and effective motor-cognitive strategies.

Repurposing is when people have stable ideas about the given problem but their environment is adaptable and can be changed to achieve their goals [18]. This relates to Kirsch and Maglio's distinction between pragmatic and epistemic actions [15]. Pragmatic actions bring people closer to their goal; epistemic actions mostly support people's ability to think about the problem. Although tokens have physical form factors and constraints that suggest ways to manipulate them, the characteristics of gestural interaction with tokens described above (space, flow, cardinality) point to ways in which TAC systems might leave room for individual customization. For example, tokens placed on-surface may have certain defined behaviors, while on-bezel or in-air interaction with the same tokens might allow users to redefine their functions, allowing each person to develop their own strategies for problem-solving.

Physically distributed learning is when people's ideas and the environment are both adaptable [18]. Here, people may interact with their environment without knowing exactly what steps they need to take or even the final state. By studying how children learn fractions with different materials, Martin and Schwartz [18] found that the emergence of new interpretations through physical adaptations of the environment is a benefit of physical action for learning abstract ideas. This suggests that system designers need not always provide tightly structured environments, but should allow people to create their own structures for problem solving. The combination of gestural interaction with active tokens can provide ways to make TAC interaction more adaptable and open-ended.

TECHNICAL CONFIGURATIONS

Here we provide a brief overview of some recent technical advancements relevant to TAC systems.

Tables, tablets, and smartphones

Interactive tables and tablets have been available in varying forms for several decades. While interactive tables have not reached the mass market, the commercial release first of Microsoft PixelSense [19], and more recently of lower-cost capacitive tables, are laying the hardware foundations for broader dissemination. Even more impactful is the pervasive consumer adoption of smartphone and tablet technologies. Many of these devices are sensor-rich and some including RFID/NFC technologies. Tablets and smartphones provide near-ready platforms for the mediation of diverse 1D and 2D constraints. Mass commercialization of inch-scale devices such as Sifteos [1] offer compelling platforms for active tokens.

Embedded computing

The last decade has witnessed explosive growth and adoption of the Arduino and Raspberry Pi processors, which offer a compelling mix of mass-market economics, mass community investment, and high-level software environments. Viewed from a TAC perspective, in synergy with mass-market tablets, such embedded tools can complement sensing and mediation capacities such as sensing on the central active surface, and on the bezels. Bezel integrations can both extend the interaction real estate of individual devices [29]; and help stitch together tiled arrays of devices.

CONCLUSION

In this paper we considered conceptual, cognitive, and technical dimensions for gestural interaction with tangible active tokens. Gestural interaction with active tokens expands the design space of tangible Token and Constraints system and offers new possibilities for learning from and understanding of large data sets.

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