Evaluating the Effect of Co-Creative Systems on Design Ideation

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Abstract

Evaluating co-creative systems is an open research question in computational co-creativity research. This paper addresses a lack of studies about evaluating the effect of co-creative systems on ideation, a creative process during which designers generate new ideas. This paper describes an approach to measuring ideation as a basis for evaluating co-creative systems in design. Particularly, we are interested in how the contribution of an AI partner in a creative design task influences design ideation in a co-creative system. In order to evaluate a co-creative design system, we present an approach for measuring ideation that has two components: an aggregate analysis and a temporal analysis. With the metrics, we hope to contribute to a critical and constructive discussion on evaluating the impact of AI contributions in other co-creative systems.

Introduction

Computational co-creative systems are a growing research area in computational creativity. While co-creative systems can be applied to a variety of domains associated with creativity and encourage designers' creative thinking, there are few studies that focus on evaluating co-creative systems. Understanding the effect of co-creative systems in the ideation process can aid in the design of co-creative systems and evaluation of the effectiveness of co-creative systems. However, most research on co-creative systems focuses on evaluating the usability and the interactive experience (Karimi et al., 2018) rather than how the co-creative system influences creativity in the creative process. To evaluate the usability and the user experience of co-creative systems, the studies often used qualitative approaches and a few studies have used a quantitative approach to evaluate the user experience of co-creative systems relying on questionnaires (Kantosalo and Riihiaho, 2019) such as the System Usability Scale (SUS) (Brooke, 1996) and the Creativity Support Index (CSI) (Cherry and Latulipe, 2014). This paper describes a quantitative approach to measure ideation as the basis for evaluating the effect of AI inspiration in a co-creative system. This quantitative approach provides generalized measure for evaluating the effect of co-creative systems in design. With these quantitative measures, researchers can quantify the effective of a co-creative system on design ideation and compare the effect of different AI models in a co-creative system.

Ideation, an idea generation process for conceptualizing a design solution, is a key step that can lead a designer to an innovative design solution in the design process. Idea generation is a process that allows designers to explore many different areas of the design solution space (Akin, 1990; Atman et al., 1999; Brophy, 2001; Cross, 2001; Liu et al., 2003). Ideation has been studied in human design tasks and collaborative tasks in which all participants are human. Collaborative ideation can help people generate more creative ideas by exposing them to ideas different from their own (Chan et al., 2017). This paper has a focus on evaluating how a co-creative agent influences the ideation process in a human-AI collaboration.

In this paper, we describe a method of measuring ideation as a basis for evaluating the effect of AI models on the design process. To measure ideation in a co-creative system, we employ two approaches: an aggregate analysis that quantifies novelty, variety, and quantity of ideas in an ideation, and a temporal analysis that focuses on the temporal changes of novelty, variety, and quantity of ideas during the design process. The contribution of this paper is a method for evaluating co-creative systems in design.

Evaluation of Computational Co-creative Systems

Evaluating co-creative systems is still an open research question and there is no standard metric for measuring computational co-creativity (Karimi et al., 2018). The research on co-creative systems shows various approaches to evaluate co-creative systems and computational co-creativity. Some researchers focus on evaluating the interactive experience and others focus on the effectiveness of the system to produce or generate a creative outcome.

Shimon (Hoffman and Weinberg, 2010) is a robotic marimba player that listens and responds to a musician in real time. The evaluation of Shimon (Hoffman and Weinberg, 2010) is a performance-based evaluation of the system. The evaluation used observation to analyze the system's behaviors and the audience reactions during the performance. Drawing Apprentice (Davis et al., 2015) is a co-

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creative drawing system in which the computational partner analyzes the user's sketch and responds to the user's sketch. Drawing Apprentice (Davis et al., 2015) focused on usability and system accuracy in the evaluation. The evaluation methods include algorithm testing, voting, survey, and retrospective protocol analysis to evaluate the system and interactive experience. Viewpoints AI (VAI) is a co-creative dance partner that analyzes the user's dance gestures and provides complimentary dance in real-time by a virtual character projected on a large display screen (Jacob et al., 2013a, 2013b). In the evaluation of Viewpoints AI (Jacob et al., 2013a, 2013b), the researchers observed how participants interact with the systems and the participants provided feedback about their interactive experiences. While these examples of evaluation focus on interactive experience in the creative process, Sentient Sketchbook (Yannakakis et al., 2014), and 3Buddy (Lucas and Martinho, 2017), co-creative systems for game level design, focused on the usefulness of the system since both systems support a goal-directed design rather than an open-ended artistic performance. The methods used include a survey, interview, and observation to measure the usefulness of the system. Our study is distinct in evaluating the impact of the AI partner on the user's ideation process.

Karimi et al. (Karimi et al., 2018) presented a framework for evaluating creativity in computational co-creative systems. This framework responds to four questions that serve to characterize the many and varied approaches to evaluating computational co-creativity: who is evaluating the creativity, what is being evaluated, when does evaluation occur, and how the evaluation is performed. The framework enables comparisons of evaluation focus and methods across existing co-creative systems. Using this framework, we have shown that the evaluations of the existing co-creative systems described in this section respond to "what is being evaluated" with a focus on evaluating the interactive experience and the final product. In this paper, we respond to "what is being evaluated" and "how is the evaluation performed" by evaluating the novelty, variety, and quantity of ideas in the ideation. Section 3 describes how we define and measure ideation in more detail.

Measuring Design Ideation When Co-creating with an AI Agent

Ideation is a creative process where designers generate, develop, and communicate new ideas. Ideation in design can lead to innovative design solutions through generating diverse concepts (Akin, 1990; Atman et al., 1999; Brophy, 2001; Cross, 2001; Liu et al., 2003). The goal of design is to develop useful and innovative solutions and design ideation allows designers to explore different areas of the design solution space (Daly et al., 2012; Newell and Simon, 1972). A design process is an evolution of different kinds of representations (Goel and Pirolli, 1992). In a design process, designers externalize and visualize their design intentions and communicate with external visualizations to interact with their internal mental images (Dorta, 2008). During ideation, designers commonly use freehand sketches and rough physical models as a tool for constructing external representations that also serve as cognitive artifacts of design (Visser, 2006). Making sketches and physical models is an interaction between the designer and the designer's ideas, similar to a conversation (Dorta, 2008). In the ideation stage, designers frame problems producing new discoveries through this conversation. The graphical and physical representations as cognitive artifacts are essential components of the ideation process.

The first step for measuring ideation is to define what an idea is in the ideation process using a co-creative system. Defining an idea in design ideation using a co-creative system is a challenge since the idea can be defined differently involving the contribution of an AI partner in ideation. In engineering design, an idea is normally considered as a possible solution to a given problem for evaluating the performance of idea generation (Shah et al., 2003). However, an idea can be variously defined as a contribution that contains task-related information, a solution in the form of a verb–object combination, and a specific benefit or difficulty related to the task (Reinig et al., 2007). To define an idea in design ideation using a co-creative system, we use a cognitive approach by collecting think aloud data and coding the data for cognitive issues. We define an idea as a cognitive issue that the designer considers during the design process, and adopt the Function-Behavior-Structure (FBS) ontology (Gero, 1990; Gero and Kannengiesser, 2004) as a basis for segmenting and coding each idea in the design process. FBS ontology is a design ontology that describes designed things, or artifacts, irrespective of the specific discipline of designing. The function (F) of a designed object is defined as its teleology; the behavior (B) of that object is either derived (Bs) or expected (Be) from the structure, where structure (S) represents the components of an object and their compositional relationships. These ontological classes are augmented by requirements (R) that come from outside the designer and description (D) that is the document of any aspect of designing. In this ontological view, the goal of designing is to transform a set of requirements and functions into a set of design descriptions. The transformation of one design issue into another is defined as a design process (Gero, 2010). We define a design idea in design ideation using a co-creative system as a cognitive issue.

To measure ideation in a co-creative system, we developed three metrics based on (Shah et al., 2003), used for evaluating idea generation in design: novelty, variety, and quantity of design. We define the effect of the co-creative system as contributions of the AI agent to the idea generation. Two basic criteria are identified to define the contributions of the AI agent based on (Shah et al., 2003):

- How well does the AI agent contribute to expanding the design space?
- How well does the AI agent contribute to exploring the design space?

We employ two approaches with the three metrics: an aggregated approach and a temporal approach. The aggregate approach allows us to evaluate the contributions of an AI agent in a design ideation. The representation of ideation process by temporal changes of ideas allows to (1) compare an ideation process of a design session to other design sessions, (2) identify specific patterns of novelty, variety, and quantity of ideas in a condition, (3) identify specific contributions of the co-creative system associated with novelty, variety, and/or quantity.

Aggregate Analysis

For the aggregate approach, we developed three metrics based on (Shah et al., 2003), used for evaluating idea generation in design: novelty, variety, and quantity of design. Novelty is a measure of how unusual or unexpected an idea is as compared to other ideas (Shah et al., 2003). A novel idea is defined as a unique idea across all design sessions in a condition. For measuring novelty, we count how many novel ideas in the entire collection of ideas in a design session then divide the novel ideas by the number of AI contributions (e.g. inspiring sketches and images that the AI agent provides) that the designer gets from a co-creative system, as shown in Equation (1). The novelty score thus means the number of novel ideas per AI contribution in a design session. Variety is a measure of the explored solution space during the idea generation process (Shah et al., 2003). The generation of similar ideas indicates low variety and hence, less probability of finding better ideas in other areas of the solution space. For measuring variety, we code each idea whether it is a new idea or a repeated idea in a design session and only the number of new ideas is counted in a design session then divide the new ideas by the number of AI contributions that the designer gets from a co-creative system, as shown in Equation (2). Quantity is the total number of ideas generated, generating more ideas increases the possibility of better ideas (Shah et al., 2003). For measuring quantity, the number of ideas both new ideas and repeated ideas is counted in a design while the metric of variety includes only new ideas, as shown in Equation (3). These metrics enable a comparison of a designer's exploration of design space while using different AI models in ideation.

1. *Novelty Score*:

$$\frac{\Sigma(\textit{Unique ideas across all design sessions in a condition})}{\Sigma(\textit{AI contributions in a design session})}$$

2. *Variety Score*:

$$\frac{\Sigma(\textit{New ideas in a design session})}{\Sigma(\textit{AI contributions in a design session})}$$

3. *Quantity Score*:

$$\frac{\Sigma(\textit{New ideas in a design session}) + \Sigma(\textit{Repeated ideas in a design session})}{\Sigma(\textit{AI contributions in a design session})}$$

Temporal Analysis

A single value for each of novelty, variety, and quantity of ideas in a design session enables of measure of ideation to be associated with the entire design session. We include a temporal analysis of ideation to enable a characterization of the flow of ideas during a design session. We divide a design session as a series of segments bounded by the input of inspiration from the AI agent. For the temporal analysis, the number of novel ideas, the variety of ideas, and the quantity of ideas are calculated for each segment to produce a sequence of temporally ordered ideas in a design session. The nuances of the ideation process are then illustrated by temporal changes of novelty, variety, and quantity of ideas over time.

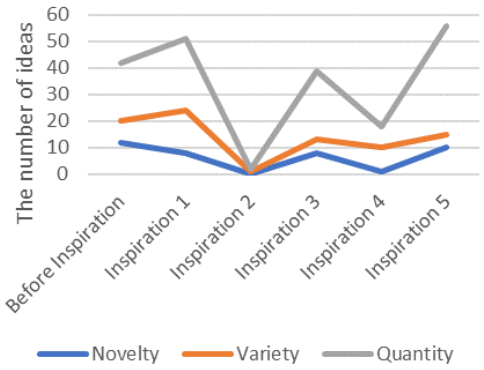

Figure 1: Example of temporal analysis

Conclusion

Measuring ideation when co-creating with an AI-based co-creative design tool enables the comparison and evaluation of the impact of different AI models on the user's cognitive process and the creative outcome. In order to measure ideation, we developed an approach for measuring ideation that has two components: an aggregate analysis and a temporal analysis. The aggregate analysis adapts existing quantitative metrics for ideation: novelty, variety, and quantity of ideas expressed in the design session. The temporal analysis shows the temporal changes of novelty, variety, and quantity of ideas based on the AI contributions. These measures can be used in evaluating the impact of AI contributions in other co-creative systems that support design creativity. We conclude that the approach that we developed for measuring ideation can allow different AI models for inspiration to be compared and justified.

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