Method for Quantification of the Process of Collaborative Creativity: Visualization of the Dynamics by C^2RQA

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Abstract

This study proposes an analytical method to visualize and quantify the process of collaborative creativity. While many studies have theoretically emphasized the importance of process in creativity, its complex nature—characterized by emergence and revisitability, representation and embodiment, and conscious and unconscious aspects—has made it difficult to quantify in a standardized way. We introduce an extended version of cross-recurrence quantification analysis, C^2RQA, as a suitable method. C^2RQA is applicable to various data types, including continuous, categorical, and binary, and can visualize correspondences between two time series, thereby revealing interaction dynamics. We applied C^2RQA to two creative activities: an idea generation task and an insight problem. The results suggest that C^2RQA effectively captures broad dynamic transitions in ideas and the underlying subconscious processes involved in collaborative creativity.

Keywords: collaborative creativity; interaction process; visualization; quantification; cross recurrence quantification analysis

Introduction

This study proposes an analytical method to visualize and quantify the creative process involving multiple individuals. We apply this method to several creative activity datasets to evaluate its effectiveness. Prior research has emphasized the importance of the creative process through which novel and useful products are generated (e.g., Besemer & O'Quin, 1986; Finke et al., 1996). For instance, the 4P's model of creativity (Rhodes, 1961) explicitly highlights the process alongside person, product, and press. More recent frameworks further stress the need to focus on the process itself, wherein creators, collaborators, and the environment interact to produce creative outcomes (Glăveanu, 2013; Clapp & Hanson, 2019; Okada & Yokochi, 2024; Sawyer & DeZutter, 2009).

What are the defining characteristics of such a process? And what kind of analysis can capture them? We address these questions with reference to prior research, focusing particularly on short-term creative processes ranging from minutes to several hours.

The first key feature is emergence and revisitability. In creative activities—often viewed as ill-defined problem-solving tasks without a single correct solution (Klahr & Dunbar, 1988; Simon & Newell, 1971)—ideas are continually generated, modified, and revisited. Ideas initially set aside may later be reintroduced or reinterpreted from new perspectives. Such dynamics have been observed in both artificial tasks (e.g., divergent thinking) and naturalistic creative work such as art and design (Jaarsveld & van Leeuwen, 2005; Okada et al., 2009; Shimizu & Okada, 2018). This cycle of emergence and revisitability, central to the definition of creativity, reflects core features of the idea generation process.

The second feature is representation and embodiment. As demonstrated in studies of scientific discovery, individuals engage in higher-order and conceptual thinking using words and images during creative activities (Dunbar, 1993; Okada & Simon, 1997; Simon & Newell, 1971). However, as seen in mathematicians' concept discovery processes, such thinking is also strongly shaped by physical embodiment and the surrounding environment. For instance, mathematicians often adjust their physical distance from the whiteboard before and after moments of insight (Tabatabaeian et al., 2024). Similarly, studies of artistic creation show that cognitive processes, bodily actions, and the perceptual experiences linking them dynamically interact during the production of artwork (Botella et al., 2013; Okada & Yokochi, 2024; Shimizu, Hirashima, & Okada, 2019). These findings illustrate how creative processes emerge through complex, active interactions between mental representation and the body.

The third feature is the interplay between conscious and subconscious processes. This aspect relates closely to the first feature, revisitability, and the second, representation and embodiment. Traditionally, creative ideas and products have been viewed as outcomes of higher-order, conscious thought (Klahr & Dunbar, 1993; Simon & Newell, 1971). However, in artistic domains such as painting and dance, unconsciously produced lines or movements—those made without clear intention—can significantly shape subsequent conscious actions (Shimizu & Okada, 2018; Okada & Yokochi, 2024; Yokochi & Okada, 2005). Similarly, qualitative studies of theatrical performance show that unintended utterances or gestures can be reinterpreted by others in later interactions, and through this accumulation, the meaning of the narrative gradually emerges (Sawyer & DeZutter, 2009). While the notion of "creator's intention" requires further conceptual clarification, these findings suggest that creativity unfolds

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through interactions between intentional and unintentional language and action.

Given the features of the creative process—emergence and revisitability, representation and embodiment, and conscious and subconscious dynamics—it is essential to capture the trajectory through which ideas are generated, developed, and revisited. This requires attention to multiple modalities, including images, language, and physical actions, and to both conscious and unconscious processes.

This study focuses on collaborative creativity, where these features are particularly evident. Prior research on collaborative creativity (e.g., Dunbar et al., 1999; Okada & Simon, 1997; Sawyer & DeZutter, 2009; Schunn & Klahr, 1993) has shown how ideas emerge and evolve through the interaction between ideational and embodied processes across individuals. However, most of these studies have examined specific moments or cases—often just prior to the generation of a key idea—rather than analyzing the entire creative process. Few have attempted to visualize and quantitatively examine the full trajectory of collaboration. One reason for this gap is the lack of appropriate analytical methods that can capture the full process in a bottom-up manner. To address this, the present study proposes a method for visualizing and quantifying collaborative creativity, grounded in the three key features discussed above.

Colored Cross Recurrence Quantification Analysis (C^{2}RQA)

In the following section, we introduce Cross Recurrence Quantification Analysis (CRQA), which forms the basis of the proposed method. Due to space constraints, detailed mathematical formulations are omitted; readers are referred to review articles for comprehensive explanations (e.g., Marwan, 2008; Marwan & Webber, 2014).

CRQA is an extension of Recurrence Quantification Analysis (RQA), developed to visualize and quantify synchronization and coordination between two time series (cf. Zbilut & Webber, 1998; Marwan & Kurths, 2002). First, in the case of categorical data, CRQA reconstructs the state space directly; for continuous data, it applies phase-space embedding. The two time series are then arranged on the vertical and horizontal axes, respectively (Figure 1, top). A two-dimensional plot, known as the Cross Recurrence Plot (CRP), is created by marking intersections where the values of the two series are identical or similar—indicating moments of synchronization or coordination. This plot visually represents the correspondence between the two time series (Figure 1, top). As this study focuses primarily on categorical data, discussions related to embedding are omitted (cf. Marwan, 2011).

Then, CRQA focuses mainly on several kinds of lines in the plot, like diagonal lines. Diagonal lines indicate the continuation of the synchronization and coordination state of the two-time series data. CRQA quantifies the frequencies and characteristics of synchronization and coordination based on the proportion and length of the lines. (Figure 1 bottom). Various quantification indicators have been proposed

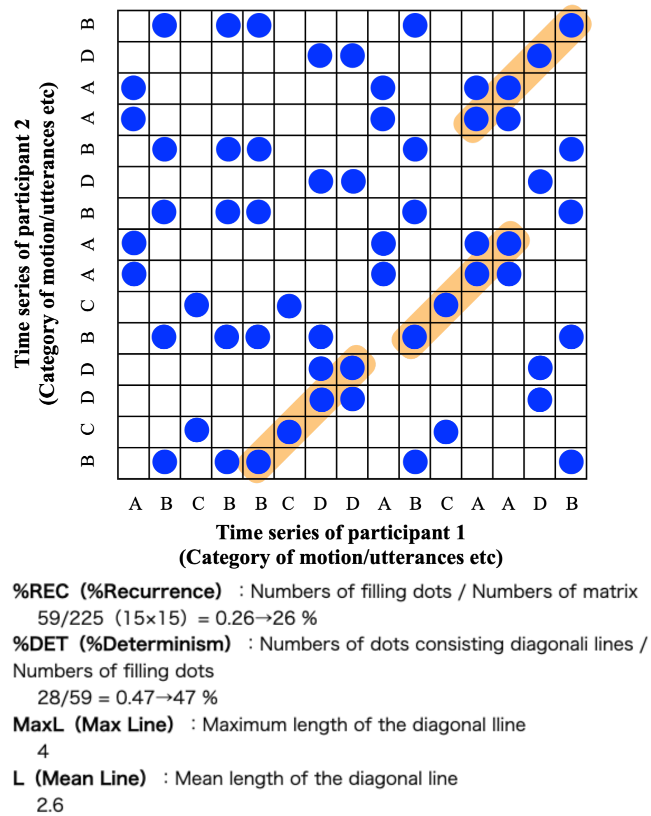


Figure 1: Outline of CRP and CRQA

(Fusaroli et al., 2014; Marwan & Kurths, 2002; Zbilut & Webber, 1998). %REC (%Recurrence, which extracts the degree of overall synchronization and coordination), %DET (%Determinism, which extracts the percentage and length of diagonal lines), MaxL (Max Line: maximum length, the maximum length of the diagonal line in the plot), L (Mean Line: mean length, the average length of the diagonal line in the plot), and ENT (Entropy: complexity of the distribution of the length of the diagonal line) are examples.

CRP/CRQA was originally developed in the 1980s within the framework of nonlinear dynamics and chaos theory and has since been applied in fields such as earth science, economics, chemistry, and physics (Marwan, 2008; Marwan & Kraemer, 2023; Marwan & Webber, 2014). Beginning in the 2000s, its use expanded to the study of multi-person interaction in physiology, psychology, and cognitive science. Examples include analyses of postural coordination during conversation (Shockley, 2005; Pellecchia & Shockley, 2005), eye movement synchronization in Tangram tasks involving verbal picture descriptions (Dale et al., 2011; Richardson et al., 2005, 2007), hand movement coordination in rock-paper-scissors games (Kodama et al., 2019), and heart rate synchronization between dancers and audience members during dance battles (Shimizu et al., 2024).

Thus, CRP/CRQA has been increasingly applied across diverse domains to visualize and quantify interpersonal interactions. In this study, we extend the method in line with the key features of the creative process and apply it to analyze the cognition and behavior of multiple individuals engaged in collaborative creativity.

We made the following three extensions to CRQA. First, based on the feature of emergence and revisitability, we color-code different ideas according to their content. While traditional CRQA typically marks all coordinated points in black, this extension allows for clearer visualization of when specific ideas are actively proposed by different participants, and it makes the transitions between ideas more transparent. Second, we extend the analysis to include multiple modalities, such as speech and physical action. This multimodal application, explored in previous studies (e.g., Wallot et al., 2018), enables the extraction of features related to representation and embodiment in the creative process. Third, building on earlier work, we compare the frequencies of recurrence above and below the diagonal. This approach reveals the directionality of interaction—identifying, for example, which participant first introduced an idea and which participant subsequently developed it. Although directionality is not explicitly included in the core features of the creative process, it plays a critical role in collaborative dynamics. Together, these extensions allow us to visualize and quantify the complex, dynamic nature of collaborative creativity.

Application of the Analysis to Several Creative Processes

In this section, we apply the proposed analysis (C²RP/ C²RQA) to two types of creative tasks commonly examined in creativity research: idea generation and insight problem solving. Due to space constraints, detailed procedural descriptions for each case are omitted.

Application to the Idea Generation

We applied the proposed analysis to a dyadic idea-generation task, a widely used paradigm for studying creative cognition (Finke et al., 1996; Ward & Smith, 1999). In this task, participants were asked to explore and generate creative solutions that meet given task requirements. Specifically, participants were instructed to "think of an idea for a new and creative museum" and to present their ideas using both illustrations and text. They were given 15 minutes to complete the task. Participants were encouraged to discuss their ideas with each other and to record their thoughts on a whiteboard. The pair consisted of two female university students (both 22 years old) majoring in dance studies, neither of whom had prior experience with similar idea-generation tasks.

The pair developed the concept of a "Moving Museum." This idea is characterized by the following two features: (A) Each artwork is presented without a title, allowing viewers to create their own interpretations and share them with others. (B) The artworks are displayed at intervals along the window frames of a moving train, enabling audiences to experience both the artworks and their associated titles in conjunction with the passing scenery as they travel through different

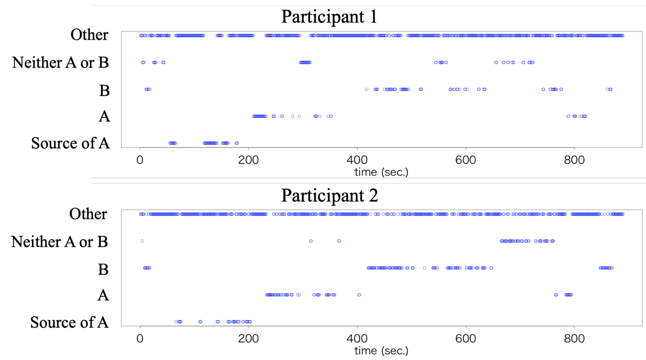


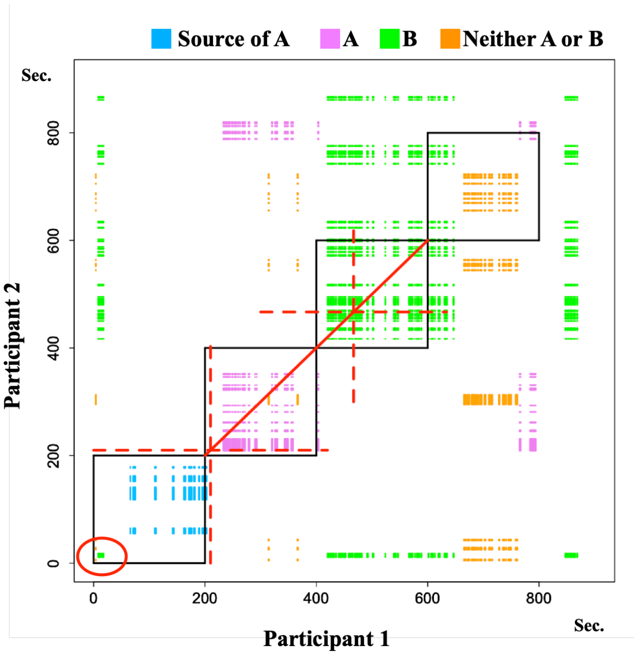
Figure 2: Categorical time series of each participant

regions. Both participants expressed strong satisfaction with the resulting concept.

The following section outlines the analysis procedure for participants' utterances and presents the results. First, all utterances were transcribed. Then, a bottom-up coding approach was used to categorize the utterances by content similarity (Figure 2). This categorization produced categorical time-series data based on the utterance content. Utterance segmentation and coding were performed using ELAN (Max Planck Institute), with each individual utterance identified and classified from the video. The analysis yielded five categories: 1: Suggestions/questions that served as the source of Feature A (e.g., the audience creates the artwork.) 2: Suggestions/questions related to Feature A (e.g., the audience assigns a title.) 3: Suggestions/questions related to Feature B (e.g., the museum travels by train.) 4: Suggestions/questions unrelated to either Feature A or B. 5: Other (e.g., no utterance or content not corresponding to Categories 1–4)

Next, a Cross Recurrence Plot (C²RP) was generated by aligning the speech time series of Participant 1 on the horizontal axis and that of Participant 2 on the vertical axis. Squares corresponding to matching categories were color-coded (Figure 3, top): blue for Category 1, purple for Category 2, green for Category 3, and orange for Category 4. Category 5 was excluded from colorization to enhance visual clarity. Additionally, red dotted crosses indicate the time points at which Feature A (210 sec) and Feature B (467 sec) were first explicitly verbalized.

We next provide a qualitative interpretation of the C²RP. The color coding in the top panel of Figure 3 clearly distinguishes the different types of ideas discussed. At the beginning of the session, both participants actively proposed and questioned ideas that later formed the basis of Feature A (Category 1). In the middle phase, ideas related to Feature A (Category 2) were generated and frequently discussed. During the latter part of the session, the discussion shifted toward ideas associated with Feature B (Category 3). In the final phase, participants discussed a number of ideas unrelated to either Feature A or B (Category 4). Based on these patterns and the content of the conversations, the idea-generation process appears to have unfolded as follows: Initially, participants exchanged many suggestions and questions that contributed to the emergence of Feature A.



Suggestions/questions for ideas that were the soruce of feature A (Blue)

	RR	DET	maxL	L	ENTR	Leader/Follower
Phase 1	3.8	92.56	6	3.38	1.46	no calculation
Phase 2	0	NA	0	0	NA	no calculation
Phase 3	0	NA	0	0	NA	no calculation
Phase 4	0	NA	0	0	NA	no calculation

Suggestions/questions for ideas related to feature A (Purple)

	RR	DET	maxL	L	ENTR	Leader/Follower
Phase 1	0	NA	0	0	NA	no calculation
Phase 2	4.94	79.25	13	3.6	1.66	below: 1681, above: 292
Phase 3	0	NA	0	0	NA	no calculation
Phase 4	0.2	90.48	4	2.71	0.96	no calculation

Suggestions/questions for ideas related to feature B (Green)

	RR	DET	maxL	L	ENTR	Leader/Follower
Phase 1	0.14	61.11	3	2.2	0.5	no calculation
Phase 2	0	NA	0	0	NA	no calculation
Phase 3	8.66	75.61	8	2.88	1.29	below: 1939, above: 1509
Phase 4	1.05	72.88	6	2.46	0.9	no calculation

Suggestions/questions for ideas not related to feature A or B (Orange)

	RR	DET	maxL	L	ENTR	Leader/Follower
Phase 1	0.03	NA	0	0	NA	no calculation
Phase 2	0.19	94.74	2	2	0	no calculation
Phase 3	0	NA	0	0	NA	no calculation
Phase 4	0.98	69.85	3	2.16	0.44	no calculation

Figure 3: Results of C^2RP and C^2RQA of idea-generation task

This was followed by an active elaboration of ideas related to Feature A. While discussing possible contexts in which audiences could implement Feature A (e.g., titling artworks), Feature B was discovered. Participants then engaged in an active exchange of ideas related to Feature B. Finally, the overall concept was refined through discussion of additional ideas not directly related to Features A or B. These observations suggest that ideas were progressively developed and refined through dynamic engagement across the four types of idea categories.

Moreover, a closer examination of the early part of the session reveals that several ideas related to Feature B (Category 3) had already appeared (Figure 3, top; green plots circled in red). This suggests that ideas later actively discussed in the second half were partially introduced during the initial phase. A detailed review of the utterances shows that, at the time, these early ideas were not treated as particularly noteworthy. However, after generating additional ideas related to Feature A (e.g., the audience titling the artwork) and reflecting on where this activity might occur, the earlier idea was reinterpreted as meaningful and further developed. This process of revisiting—where an idea is reconsidered and repurposed in light of subsequent ideas—demonstrates a key strength of the proposed analysis: its ability to reveal non-linear, iterative dynamics in collaborative creativity.

We also examined the leader–follower dynamics between participants. The periods during which Features A and B were actively discussed are separated by a red diagonal line in the plot. For Feature A (indicated by clusters of purple plots), more points appear below the diagonal than above, suggesting that Participant 2 initiated suggestions and questions, to which Participant 1 responded. In contrast, for Feature B (green plot clusters), a roughly equal number of points appear above and below the diagonal, indicating that both participants contributed suggestions and responses more evenly. These findings suggest that for Feature A, Participant 2 took the lead in shaping the idea. For Feature B, however, both participants appeared to engage more collaboratively. Given the revisitability of Feature B—having been introduced earlier in the session—both participants already shared some understanding of the idea. This likely enabled them to jointly contribute suggestions and questions in a more balanced manner.

The C^2RQA values, derived from the quantification of the C^2RP (Figure 3, bottom), further support these findings. The results show that the frequency of synchronization and coordination for each category—measured by the co-occurrence of category mentions between the two participants—varied significantly across phases divided at the 200-second mark. Additionally, ideas related to Feature B were indeed present in the initial phase, consistent with the observed revisitability. The leader–follower dynamics also differed between Category 2 (related to Feature A) and Category 3 (related to Feature B). While further studies with a larger sample of participant pairs are needed, this analysis clearly demonstrates the capacity of C^2RQA to visualize and quantify key characteristics of the collaborative idea-generation process, including emergence, revisitability, and lead–follow relationships.

Application to the Insight Problem

Next, we applied the proposed analysis to a task in which a pair worked collaboratively on an insight problem. Insight problems require individuals to overcome implicit constraints that block potential solutions (Ohlsson, 1992; Knoblich et al., 1999), often involving a sudden realization of the solution during the problem-solving process.

In this study, we used the T-puzzle, in which participants must form a T-shape using four given pieces (Figure 5). Previous research has identified two primary constraints that hinder successful completion: (1) the tendency to fill the dent of the pentagonal piece A (Constraint 1), and (2) the tendency

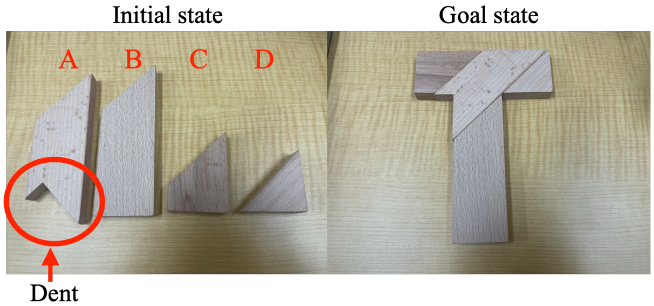


Figure 4: Outline of T puzzle

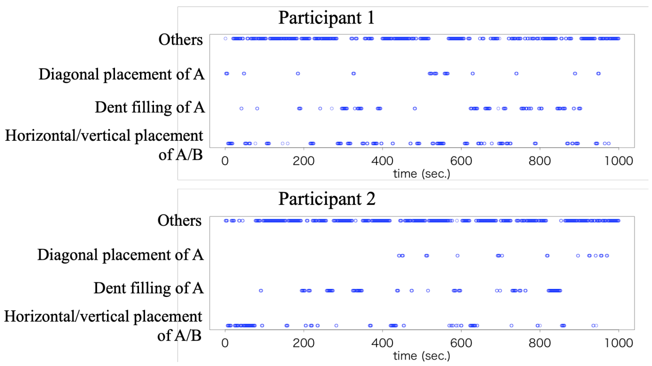
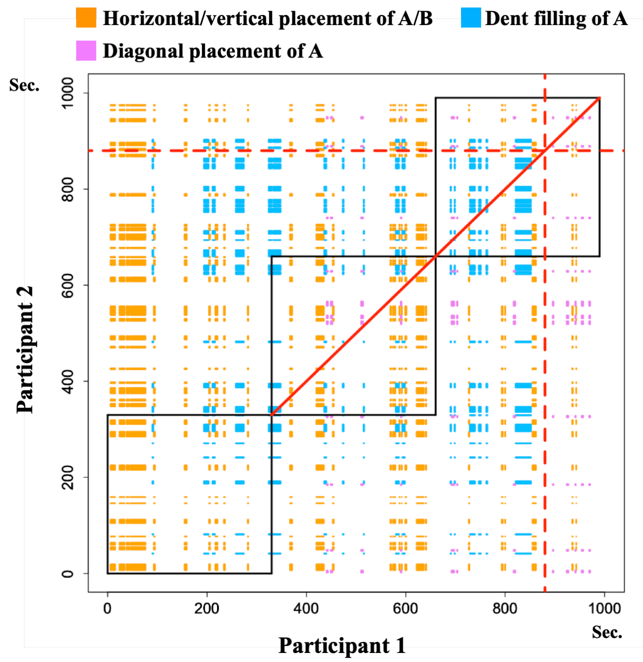


Figure 5: Categorical time series of each participant

to arrange parts A or B in vertical or horizontal orientations (Constraint 2). These constraints are thought to gradually relax through repeated unsuccessful attempts, eventually leading to an increased frequency of placing part A diagonally (Suzuki et al., 1999). The participants were the same two university students who took part in the idea-generation task. Neither had prior experience with the T-puzzle. They were given 25 minutes to complete the task.

We begin by summarizing the problem-solving outcome. Based on video analysis, the participants reached the correct solution at 990 seconds. Prior to that point, their conversation indicated that they had not recognized the importance of placing part A diagonally. This observation was further supported by retrospective interviews, in which both participants explicitly stated that they did not realize the significance of the diagonal placement of part A until the moment they arrived at the solution.

Next, we analyzed participants' part-manipulation behavior using C^2RP/ C^2RQA to visualize and quantify behavioral correspondence (Figure 5). The overall procedure followed the same steps as in the idea-generation task, with the exception that video footage was used as the data source. While viewing the video, each participant's manipulation of puzzle parts was categorized into four types: (1) placing parts A and B vertically or horizontally, (2) filling the dent in part A, (3) placing part A diagonally, and (4) other manipulations (Figure 5). Drawing on previous research, we defined Categories (1) and (2) as actions constrained by prior assumptions, and Category (3) as an unconstrained action. Using ELAN, we coded these behaviors on a one-second time scale. The manipulation time series of Participant 1 was



Placing part A/B vertically or horizontally (Yellow)

	RR	DET	maxL	L	ENTR	Leader/Follower
Phase 1	4.72	92.66	13	4.94	2.13	no calculation
Phase 2	3.99	92.13	16	3.62	1.67	no calculation
Phase 3	0.84	77.78	8	2.83	1.24	no calculation

Filling the dent in part A (Blue)

	RR	DET	maxL	L	ENTR	Leader/Follower
Phase 1	1.18	92.02	15	3.79	1.63	no calculation
Phase 2	1.47	93.81	12	4.35	1.97	no calculation
Phase 3	3.74	95.11	13	4.39	1.98	no calculation

Placing part A diagonally (Purple)

	RR	DET	maxL	L	ENTR	Leader/Follower
Phase 1	0	NA	0	0	NA	no calculation
Phase 2	0.35	91.53	5	2.98	1.27	below: 98, above: 280
Phase 3	0.25	82.22	4	2.49	0.87	below: 91, above: 179

Figure 6: Results of C^2RP and C^2RQA of insight problem

plotted on the horizontal axis, and that of Participant 2 on the vertical axis. A C^2RP was then generated by marking cells where the same behavior category occurred with specific colors: yellow for vertical/horizontal placement (Category 1), blue for dent filling (Category 2), and purple for diagonal placement (Category 3). For visual clarity, Category 4 was not color-coded. A red dotted cross marks the time point (880 seconds) when one participant explicitly verbalized the importance of placing part A diagonally. The entire session was divided into three 330-second phases, separated by black lines.

The following provides a qualitative interpretation of the C^2RP. As shown in the top panel of Figure 6, during Phase 1, part manipulations constrained by prior assumptions (Categories 1 and 2) were frequently observed. In contrast, unconstrained manipulations (Category 3) were not performed jointly by both participants. However, an individual analysis of the time series revealed that Participant 2 engaged in Category 3 manipulations several times early in Phase 1. This suggests that Participant 2 explored constraint-breaking behaviors independently, though without recognizing their importance—and importantly, these attempts were not picked up or developed by Participant 1. In

Phase 2 (331–660 sec), unconstrained manipulations (purple plots) were occasionally performed by both participants, even prior to their explicit recognition of the importance of this strategy. In Phase 3, the frequency of constraint-bound manipulations (Category 1: yellow) dropped markedly, while instances of constraint-breaking behavior (Category 3) increased, occurring intermittently even before the verbal acknowledgment of their significance at 880 seconds. Following this point—marked by the red dotted cross—Category 3 manipulations became dominant. These results suggest that the C^2RP effectively visualizes the gradual and intermittent emergence of constraint relaxation, as well as the evolving behavioral alignment between participants.

Additionally, we examined the leader–follower dynamics in participants' manipulations. Phases 2 and 3 were separated by a red diagonal line in the C^2RP. In Phase 2, constraint-deviating manipulations (Category 3; purple plots) appeared exclusively above the diagonal, indicating that Participant 1 initiated these actions while Participant 2 followed with a delay. In contrast, during Phase 3—particularly after the participants explicitly recognized the importance of this manipulation—purple plots appeared both above and below the diagonal. These results suggest that prior to realizing the significance of the constraint-deviating strategy, manipulation was unidirectional, led primarily by Participant 1. After this realization, however, both participants engaged in the strategy interactively and reciprocally. This shift reflects a transition from asymmetrical to symmetrical coordination. The strength of the proposed analysis lies in its ability to reveal such nuanced changes in the directionality of interaction, offering valuable insight into the dynamic leader–follower relationships that shape collaborative creativity.

The C^2RQA results further support these findings (Figure 6, bottom). Constraint-based manipulations (Category 1) were frequently observed during Phases 1 and 2, but their frequency dropped significantly in Phase 3. In contrast, constraint-deviating manipulations (Category 3) were absent in Phase 1 but appeared more frequently in Phases 2 and 3. Regarding the leader–follower relationship, a clear unidirectional dynamic was observed in Phase 2, with one participant consistently initiating constraint-deviating manipulations. However, in Phase 3, these manipulations occurred bidirectionally, indicating more reciprocal interaction.

As with the idea-generation task, further investigation with a larger sample of participant pairs is needed. Nonetheless, this analysis demonstrates strong potential for visualizing and quantifying key features of collaborative insight problem-solving—including shifts in solution strategies, the process of constraint relaxation, and evolving leader–follower dynamics.

Discussion

This study proposed C^2RQA as a method to visualize and quantify the process of creative activity involving multiple individuals. Its effectiveness was examined by applying it to data from two types of creative tasks: idea generation and insight problem solving. The results demonstrate that C^2RQA can capture key features of the creative process, including the generation and revisitation of ideas, subconscious actions not immediately recognized as important, and the directional dynamics of interaction between participants. Importantly, C^2RQA enables the tracking of these features throughout the entire creative process.

Moreover, the analysis proved applicable to both speech and action data, highlighting its flexibility in handling binary, categorical, and continuous time series. This makes C^2RQA suitable for analyzing a wide range of modalities in creative activity. Additionally, although not explored in this study, future research could apply J^2RP—an integrated recurrence plot across multiple media (Marwan, 2008)—to directly extract cross-modal idea patterns, such as those co-occurring in speech and action. In sum, the proposed analysis offers a powerful approach for visualizing and quantifying core dimensions of collaborative creativity: emergence and revisitability, representation and embodiment, and the interplay between conscious and subconscious processes.

Finally, we discuss the limitations and prospects. This study applied the proposed analysis to only one pair to examine its effectiveness, so generalizability could not be tested using significance or Bayesian methods. However, the process of collaborative creativity was quantifiable using C^2RQA. Applying this analysis to more participants would enable comparisons across phases or conditions. Moreover, it is theoretically possible to examine the relationship between C^2RQA values and product characteristics or evaluations (e.g., CAT in Amabile et al., 1986; novelty/usefulness ratings in Finke et al., 1996) using Linear Mixed Models. This would allow us to explore which process features lead to which product qualities. In future work, we plan to analyze data from more participants to investigate this relationship.

Furthermore, the proposed C^2RQA can be applied to creative activities in natural settings, such as company meetings, multi-artist collaborations, and creativity workshops. The detailed process by which ideas and works are generated, changed, and developed in each context can be quantitatively examined by focusing on multiple media such as words and actions. For example, how do multiple artists and dancers complete their artworks and performances? By classifying their drawings and movements and visualizing their correspondence through C^2RQA, we can capture the transition of their interaction.

In the near future, we plan to investigate various creative activity processes and products by targeting more pairs and to demonstrate more clearly the effectiveness of this analysis.

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