Recurrence Quantification Analysis for Group Eye Tracking Data

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Abstract. Traditional eye tracking methodologies have largely focused on single-user data. The study of multi-user dynamics and social interaction requires a novel analysis framework, partially addressed in current research. In this study, we introduce Group Eye Tracking (GET) as a framework for simultaneously collecting and analyzing eye movement data from multiple participants to reveal group-level patterns of visual dynamics. We use a custom application, which synchronously records eye movements from multiple users performing tasks on separate computers, and a custom R package implementing Recurrence Quantification Analysis (RQA) for examining time-series recurrences of visual dynamics. By quantifying how eye movement patterns recur and align among group members, we potentially provide indicators of cognitive states in collaborative decision-making, within real-time group interactions. The resulting measures can also provide information about the role of task parameters, interface layouts, and team performance. This approach demonstrates how GET can serve for developing next-generation augmented cognition systems by integrating advanced analytics and real-time adaptivity by the analysis of collective task outcomes.

Keywords: Group Eye Tracking · Recurrence Quantification Analysis · Decision Making · Eye Tracking Visualization

1 Introduction

Gathering in groups is a frequent, everyday occurrence in human societies, where collective decisions and actions are commonplace [5, 11]. The research on group dynamics has attracted interdisciplinary interest, focusing on how actions, processes, and transformations take place among individuals. The study of group dynamics has been a broad research field that addresses numerous aspects of interaction in social settings [11]. In efforts to quantify group dynamics, researchers often utilize spatiotemporal analyses [27], identify swarming patterns [38], and examine dynamic coupling mechanisms [32, 33] through data-driven models [14, 28] and agent-based models [21].

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The present study employs the Group Eye Tracking (GET) paradigm that investigates group dynamics in a collaborative visual search task [2]. For this, we offer a set of GET measures for the quantification of group dynamics. We also report on an experiment designed for the study of group dynamics in the visual search task setting. In the experiment, a group of participants synchronously performed a visual search task on multiple computers, while their eye movements were recorded synchronously. The recorded data consisted of gaze locations of the participants on the displays, collected using eye tracking devices in a group eye tracking environment, designed for the purpose of the study.

Previous studies on the use of eye tracking in collaborative tasks have employed various settings, including two participants on a single screen [29], multiple participants watching a stimulus video [36], dyadic settings with real-time mutual gaze perception [34], and mobile eye tracking to assess joint attention [32, 33]. In some of these settings, the cross-recurrence quantification analysis (RQA) has been used for quantifying spatiotemporal coordination between the eye gaze patterns of the dyads, in particular in dual eye tracking experiments [15, 16, 20, 31].

The analysis of eye tracking data in team collaboration settings has been a recently emerging field of research [1, 27, 30]. The present study aims to expand those cross-recurrence quantification analyses, a non-linear time series analysis technique, to larger groups of participants [47]. The proposed method introduces novel measures for the analysis of group eye tracking data, in addition to providing insights into group dynamics in the collaborative visual search task.

We report a comparative analysis of the RQA measures in the context of the experiment conducted, which used a 2×3 within-subject experimental design. One of the experimental design factors was the absence or presence of a visual representation of others' gaze on the screen (viz., the absence and presence of gaze location markers). The other design factor was the visibility of the visual search target (a dot with a fixed radius of a few pixels) with three conditions (dark in color, light in color, or transparent).

The main research question of the present study is to investigate the extent to which the proposed measures are applicable to quantifying group eye tracking data. We expected that visual search would be more difficult for the participants as the visual saliency of the target object was reduced (cf. The visibility of the visual search target). The loss of visibility of the target object would result in a more widespread distribution of the participants' gaze at a given moment of time. Accordingly, the decoupling of the participants' gaze locations would increase when the target was relatively transparent. We also expected that the presence and absence of gaze location markers (i.e., the other participants' gaze locations during the visual search task) would have an impact on the structural complexity of the gaze patterns. We investigated those expectations by applying the proposed group eye tracking measures to groups of two different sizes (in this case, groups of three and five participants).

The paper is organized as follows. The next section presents the concept of cross-recurrence quantification analysis. Then we introduce the Group Eye Tracking (GET) paradigm, the experiment, and data analysis. The final section discusses the findings, limitations of the study, and topics for future research.

2 Recurrence Quantification Analysis

The behavior of systems through time is usually analyzed by time-series methods, employing linear and nonlinear techniques. Linear methods often consider the non-linearities of the system dynamics as *noise*, and most nonlinear methods assume that the system is stationary. However, most ubiquitous systems are nonstationary and non-linear. The Recurrence Quantification Analysis (RQA) has been proposed as a methodology to overcome those limitations, which has also been a practice in multiple fields of research [47]. RQA has vast application areas including the study of road traffic, biopolymers, seismology, respiratory and cardiovascular systems, epilepsy, brain dynamics, interpersonal dynamics, motor coordination in autistic and healthy individuals, and processes and products of discourse to name a few [45–47].

In eye tracking research, RQA has been used as an analysis method to investigate various topics, such as expert vs. novice behavior and the characterization of fixation sequences [3, 39]. Although RQA has been used to explore various aspects of social interaction, most studies focus on dyads, and expanding RQA methods to larger groups remains a challenge [12]. One of the first applications of multidimensional and temporally windowed use of RQA was demonstrated on multichannel EEG data for the detection of epilepsy [48]. Such extensions have allowed researchers to investigate group dynamics in terms of recurrence patterns observed in the aggregated time series of group members [17].

Multidimensional extensions of RQA (e.g., MdRQA) have been proposed, for instance, to explore the coupling relationships between three or more time series, demonstrating a domain-specific application to quantify coordination between skin conductance measurements of triads as a measure of group arousal [44]. A similar multidimensional extension has also been used to investigate multimodal recurrence relationships across heart rate, postural sway, and hand movements of dyads [35, 42] and physiological synchrony dynamics in terms of electrodermal responses of collaborative learners [7].

Various variations of the RQA method have been designed for different purposes and with different strengths. For example, the mdRQA method is a multivariate extension of RQA. Unlike RQA, which accepts one variable (i.e., observation), mdRQA accepts multiple variables and thus can have two interpretations: on the one hand, one can interpret the results as a description of the dynamics of a multidimensional system in which multiple dimensions are observed. On the other hand, mdRQA can be interpreted as capturing synergistic relationships or couplings between multiple variables from different systems. The former situation does not apply to our study on group eye tracking due to the presence of multiple systems. In the latter situation, mdRQA treats multiple variables of different systems as one large system. Although mdRQA captures the coupling between variables effectively, it is not conceptually compatible with group eye tracking. The underlying reason is that the assignment of a time series of the gaze locations of a participant to each input variable of mdRQA leads to the mdRQA output of the recurrences of a single multidimensional trajectory of the system with itself (that is, a multidimensional trajectory made up of multiple, possibly multidimensional trajectories of multiple systems, i.e., multiple participants). However, coincidences (i.e., recurrences) of multiple, possibly multidimensional trajectories of multiple systems (i.e., participants) are needed with one another. As the authors of the mdRQA report, “it is not possible to calculate time-lagged coupling between signals to investigate leader-follower relationships among the component variables as with CRQA" [44], pointing to the need for a further development of the methodology.

An extension to mdRQA, called mdCRQA "extends mdRQA to bi-variate cases to allow for the quantification of the co-evolution of two multidimensional time-series". The mdCRQA extension is also not fully compatible with group eye tracking, since it does not allow for the investigation of the evolution of three and five time series (as reported in the experiment below), and arbitrarily larger groups in the future [43]. Another method akin to mdCRQA, called MMDCRQA (Multidimensional Multiscale Cross Recurrence Quantification Analysis) does not fully capture the group eye tracking paradigm either since it was designed to analyze two multidimensional time series, as mdCRQA, albeit in different time scales. To the best of our knowledge, a multidimensional extension of RQA has not been used to investigate group eye tracking as a measure of group dynamics. [49] provide definitions and procedures to quantify RP (and its various extensions, for example, CRP) structures based on previous research [13, 25, 26].

The term *recurrence quantification analysis* (RQA) was coined by Zbilut and Webber [48]. They defined five recurrence variables as complexity measures as part of the RQA, including percent recurrence (i.e. the density of recurrent points, viz. RR), percent determinism (i.e. percent of recurrent points forming diagonal segments away from the main diagonal, viz. DET), entropy of line length distribution (viz. ENT), maxline (i.e. the length of the largest line segment, viz. Dmax), and trend (i.e. measure of the paling of recurrent points away from the central diagonal). These measures were based on diagonal line structures [47]. The following section presents the Group Eye Tracking (GET) paradigm, where we applied the RQA methodology for the investigation of group.

3 The Group Eye Tracking (GET) Paradigm

The GET paradigm is a methodology developed for investigating group dynamics, by using eye tracking in group settings. This goal has been achieved using the Group Eye Tracking (GET) data collection framework, called `GETapp` (an application written by the first author in the JavaScript language)[1]. The `GETapp` was designed to be generic, meaning that it is not specific to the experiment in the present study. The system is made up of three sets of physical components: The server computer (referred to as server from now on), the client computers (henceforth clients) and the eye trackers (in our case, Eyetribe eye trackers with 60 Hz. Recording capacity)[2]. Each client computer has an eye tracking device connected to it, which in turn is run by a server program on the client computer (Fig. 1).

The eye tracking data is transferred from all the eye tracker servers directly to the eye tracking server. The server receives streams of data and, while recording them to a file, also broadcasts them back to all the clients at once. In this way, each client receives

[1] The application has reached its functional state thanks to the efforts of Mine Cuneyitoglu Ozkul for her review, bug fixing, refactoring, checking the robustness of the code, and designing and implementing the visualization module.

[2] Eyetribe eye trackers are now obsolete. However, the GETapp has been developed for processing raw eye tracking data; therefore, it is independent of the use of specific eye trackers.

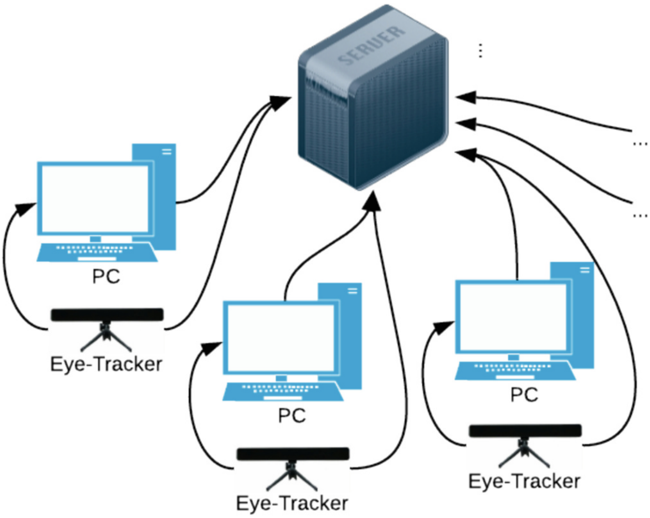

Fig. 1. Three client computers connected to the eye tracking server. An eye tracker is connected to each client and runs a server program on it.

all the data that other clients send to the server in real-time so that each participant can see where the other participants are gazing on their display.

A component of the experiment on this platform is the visualization modality (previously mentioned as the "gaze location marker"). This visualization modality may be represented as a marker, in the shape of a circle, a plus sign, a heat map, or a custom-made marker. The gaze location marker shows the gaze fixations of all the participants in real-time. It is possible to visualize the gaze location markers separately for each participant so that a participant sees multiple markers moving on the screen simultaneously.

A user interaction challenge in selecting the visualization method is the resulting clutter on the screen, due to wobbling movements of the marker. For instance, a visually sharp gaze marker (such as a cross icon) displaying others' gaze locations in real-time usually distracts user's attention. An alternative visualization method is to display the mean location of all the gaze fixations. In this case, the gaze location marker is not a direct representation of the gaze location of all the participants but is an indicator of their weighted gaze locations. A geometric mean of the fixation locations can be used for driving such a visualization marker. We call this visualization modality, which is available in `GETapp`, the *fluid gaze location marker* (Fig. 2). The fluid gaze location marker is a colored semitransparent circle. The center of the circle is the geometric mean of the gaze positions, and its diameter is a function of the standard deviation of the gaze positions from the mean. As the circle grows in size, its color becomes lighter (Fig. 2).

In the present study, we employ the fluid gaze location marker by assuming that it draws the participants' attention to a location where other participants are mostly gazing at. Further investigation of guiding by the fluid gaze location marker is beyond the scope of the present study. In the next section, we present the `generalRQA` package, which is an implementation of the methodology introduced in the previous.

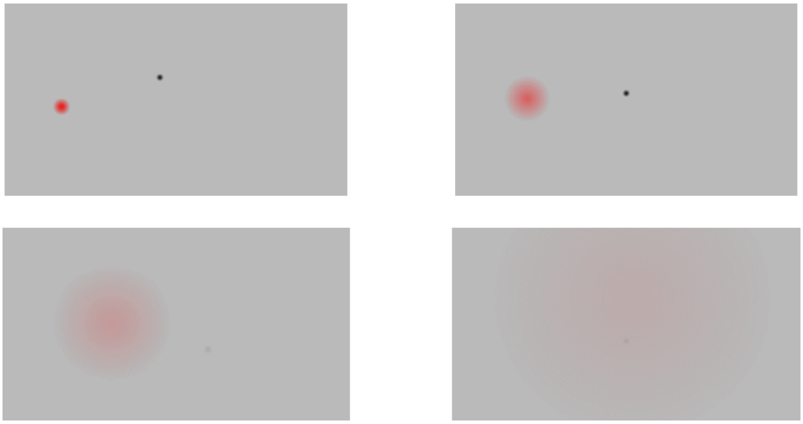

Fig. 2. The fluid gaze location marker visualization modality. The black dot (top-left and top-right) and its more transparent versions represent the target object of the visual search.

4 The `GeneralRQA` Package

The `generalRQA` package has been developed by the authors of the present study, and used for the analysis of the data reported below. There exist other packages in the R community written for recurrence analysis, such as the `crqa` package [4]. However, the available packages work with recurrence matrices of only two dimensions, whereas the goal in the present study is to analyze multiple time series concurrently. The `generalRQA` package can be used to implement cross recurrence quantification analysis (CRQA), joint recurrence quantification analysis (JRQA), and simple recurrence quantification analysis (RQA).

The general workflow of CRQA involves embedding the data, creating a distance matrix from the trajectories, creating a recurrence matrix from the distance matrix, choosing which line (or lines) parallel to the main diagonal in the matrix to work on, creating line histograms for each diagonal line and calculating the RQA measures for each of them (Fig. 3). In simple RQA, the length histogram of the entire recurrence matrix is used to calculate recurrence measures, while in CRQA, one may need to investigate the length histogram of individual diagonal lines to analyze concurrent behavior among multiple time series [24]. In this case, each diagonal line corresponds to a specific lag combination among the time series.

The input to the workflow is comprised of time-series data; each corresponding to one single participant. The time series are then transformed through the workflow to make a final recurrence matrix of which the user of the package can choose the main diagonal, or any other diagonal line parallel to the main diagonal (or multiple diagonal lines, or even the whole recurrence matrix). The output of the package, the CRQA measures, is computed from the selected diagonal lines.

In deriving these measures for our experimental data, as will be explained later, the resulting cross-recurrence plot is three dimensional for groups of three and five dimensional for groups of five participants, and hence impractical for the first case and impossible for the second case to visualize. In the following section, we demonstrate the use of the `generalRQA` package for data analysis in the context of empirical investigation.

5 Data Collection and Analysis

We recorded eye tracking data from six groups of three participants and six groups of five participants. All participants were university students (mean age $M = 23.0$, $SD = 3.11$, 28 females). They had either normal or corrected-to-normal vision. The participants were admitted into the room in groups, and each participant was seated in front of a separate computer.

Prior to the experiment, participants were informed that they would perform a visual search task where they would see a gaze location marker, which represented the average of other participants' gaze locations. However, they were not informed that the visual target would be transparent under certain experimental conditions. The goal of hiding this information was to ensure that they would pursue the visual search task. After calibration, in the experiment session, participants searched for the visual target. As introduced above, the visual target was manipulated by three experiment design conditions (i.e., visual target intensity with three conditions). It was black, gray, or transparent. The other experimental factor was the presence or absence of the gaze location marker, that is, two conditions. Consequently, the experiment had a 2 x 3 within-subject design.

Participants were instructed to click the left mouse button (it did not matter where they clicked on the screen) once they found the visual search target. When all participants clicked, they proceeded to the next screen. The session was made up of 23 trials in a single-block design. The first three trials were warm-ups, and the rest displayed the experimental conditions in random order. The participants in the groups of three were different from the participants in the groups of five, so there was no overlap between the groups in terms of participants. The visual search target appeared at any location on the screen in random order. The location of fixation is the independent variable.

RQA Measures. This section introduces the dependent variables, which are the derived RQA measures

Recurrence Rate (RR).

$$RR(\varepsilon, N) = \frac{1}{N}\sum\nolimits_{i=1,j=1}^{N} CR_{i,j}^{x,y}(\varepsilon)$$

Also known as Percent Recurrence (REC) in the literature, the *Recurrence Rate (RR)* is a measure of the relative density of the recurrence points in the recurrence matrix and is related to the correlation sum [11]. In this formulation, CR is the cross-recurrence matrix, ε is recurrence threshold, N is the number of cells in the recurrence matrix, and i and j are the indices of the matrix. The x and y superscripts on the CR matrix signify that the matrix is constructed from two different time-series. The RR merely counts the black dots (or the cells with value 1) in the CRP.

The other measures, presented below, are based on the line structures in the CRP (Cross Recurrence Plot). To define these measures, we first need to construct a histogram of the lengths of the diagonal lines in the CRP, as shown below.

$$H_D(l) = \sum\nolimits_{i=1,j=1}^{N}\left(1 - CR_{i-1,j-1}\right)\left(1 - CR_{i+1,j+1}\right)\prod\nolimits_{k=0}^{l-1} CR_{i+k,j+k}$$

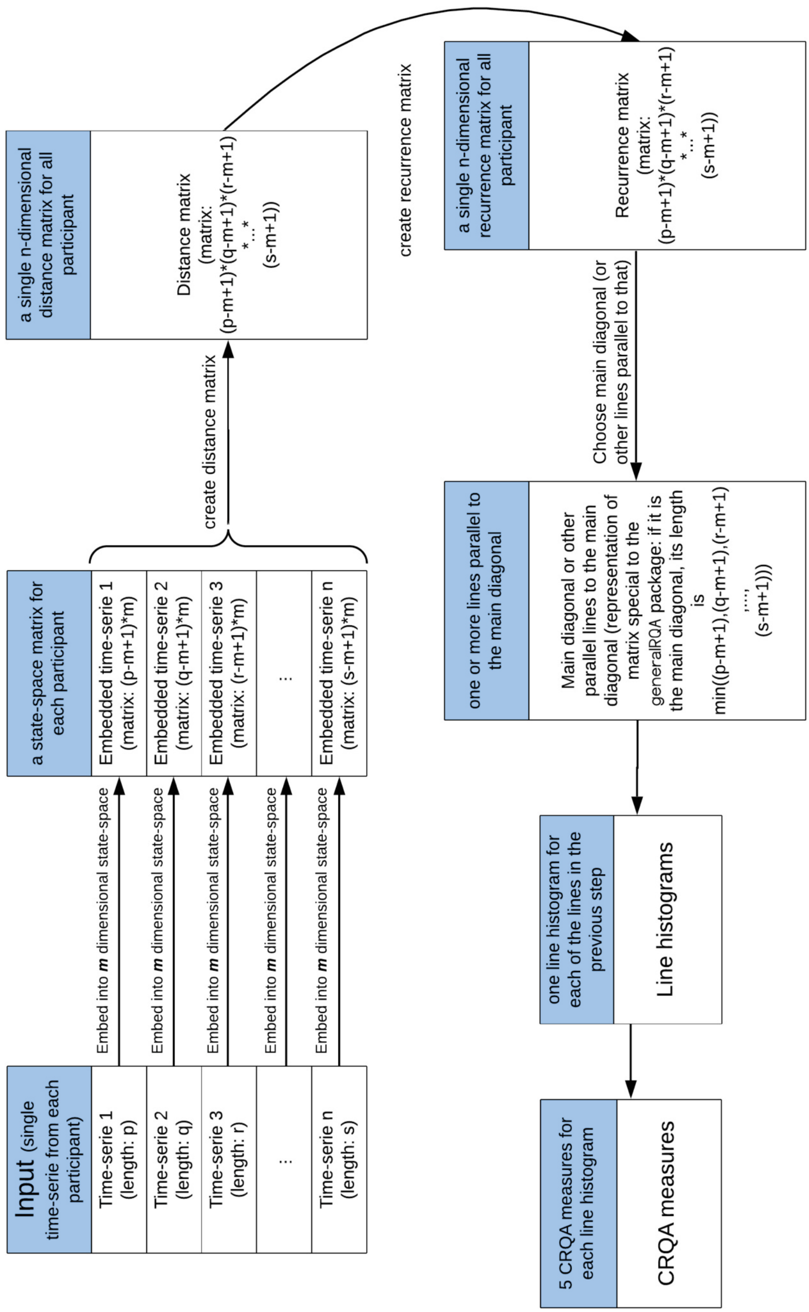

Fig. 3. The general workflow of the `generalRQA` package.

where l is the length of the diagonal line under consideration.

Percent Determinism (DET). It is defined as the ratio of the recurrence points that make diagonal lines to all the recurrence points.

$$DET = \frac{\sum_{l=d_{min}}^{N} lH_D(l)}{\sum_{i=1,j=1}^{N} CR_{i,j}}$$

DET can be interpreted as the predictability of the system. A higher *DET* value would indicate the longer times the two systems spend in synchronization. In the formulation, d_{min} sets the lower bound on the definition of a line. Typically, d_{min} is set to 2. If d_{min} is set to 1, *DET* and *RR* would be identical.

Maximal Line Length in the Diagonal Direction (D_{max}). It is the length of the longest diagonal line within the CRP.

$$D_{max} = \underset{l}{argmax} H_D(l)$$

Since the diagonal lines designate segments of the trajectories of the two systems that run in parallel, this measure indicates the divergence of the two systems' trajectories. This means that the smaller the D_{max}, the more divergent the trajectories. *AvD* (*Average Line Length in the Diagonal Direction*) is closely related to D_{max} since it is the average diagonal line length in the CRP.

Shannon Entropy of the Frequency Distribution of the Diagonal Line Lengths (ENT).

$$ENT = -\sum_{l=d_{min}}^{N} p(l) ln p(l) where p(l) = \frac{H_D(l)}{\sum_{l=d_{min}}^{N} H_D(l)}$$

where *p(l)* is the probability of a diagonal line with length *l* occurring in the cross-recurrence plot. The *ENT* is a measure of the complexity of the deterministic structure in the interaction between the two systems.

Results. A repeated measures ANOVA test was conducted for the three and five-participant groups to measure the experimental design conditions in the RQA measures, namely, *RR* (Recurrence Rate), *DET* (Percent Determinism), *ENT* (Shannon Entropy), D_{max} (Maximum Line Length), and *AvD* (Average Line Length) measures.

As it happens in eye tracking data collection settings, it is likely that eye tracker may lose calibration during data recording, in which case the time series recorded for these participants become corrupt and unusable. In cases where the time series for more than one participant were corrupt, the corresponding trial was excluded entirely, while, in the case of only one corrupt time series, either the corresponding trial was excluded entirely (the *Exclusion* approach), or the corrupt time series was replaced by the mean of all the other time series in the trial (the *Replacement* approach). Table 1 shows whether the intensity of the visual target (i.e., Point Color), the presence or absence of the gaze location marker (viz. Modality), and the group size have a significant effect on the values of the five CRQA measures.

	Point Color		Modality		Group Size	
	Exclusion	Replacement	Exclusion	Replacement	Exclusion	Replacement
RR	✓	✓	✓	✓	✓	x
DET	x	x	x	✓	✓	x
ENT	x	x	x	✓	✓	x
D_{max}	x	x	✓	✓	✓	x
AvD	x	x	✓	✓	✓	x

These findings showed that *DET* and *ENT* returned similar results under the two data processing assumptions (Exclusion and Replacement). Similarly, D_{max} and *AvD* returned comparable results, whereas the results obtained from the *RR* variable were different than the others. Among all of the measures, only *RR* revealed coherent results under all the experimental conditions.

6 Discussion and Conclusion

The goal of the present study is to quantify group dynamics in a collaborative visual search task. We investigated this in an experimental study, which aimed to differentiate between various experimental conditions based on the various coupling dynamics of group members. For this, we evaluated alternative measures to describe the group formation patterns of eye movements in a visual search task. RR was the only measure that reliably identified the experimental conditions. Consequently, the RR measure can be conceived as a reliable one for measuring visual dynamics in group eye tracking.

It is shown that in some cases and circumstances, an unembedded RP can contain all the information that its embedded versions contain [22]. Bearing this in mind and the fact that the time series for the cases with gray and black gaze targets are not long enough and yield meaningless embeddings, we decided not to embed our individual time series. However, to compare the results, we then concatenated the time-series from different participants, yielding a time-series long enough for embedding to compare the results. The outcome of the RQA on the embedded data supported our findings by revealing similar results to the non-embedded data set.

In proposing ways to find appropriate measures for group formation patterns, we have only considered four of the five classic RQA measures (Dmax and AvD considered the same measure). The other classic measure is the TREND (TND). Other than these traditional measures named by [47], the five extended measures and other more modern measures have been proposed by them. A modern approach is to consider the recurrence matrix as the adjacency matrix of a network. This allows us to use measures from the complex networks toolbox, such as clustering coefficient, betweenness coefficient, and average shortest path [8–10, 23]. In future work, these measures may also be considered as candidates for capturing group eye tracking dynamics.

Another aspect that can be considered in future work is the use of gaze location markers with different shapes. In the current study, we used a heat-map-like gaze location marker; however, the complex dynamics of the heat-map gaze location marker could have resulted in a convoluted dataset. More research is needed to study the impact of alternative visualizations on group dynamics in group eye tracking [6, 18, 19, 37, 40, 41].

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References

1. Abitino, A., Pugh, S.L., Peacock, C.E., D'Mello, S.K.: Eye TO Eye: Gaze patterns predict remote collaborative problem-solving behaviors in triads. In: International Conference on Artificial Intelligence in Education, pp. 378–389. Springer International Publishing, Cham (2022)
2. C Acartürk M Fal MP Çakır 2024 User performance and engagement in multi-user gaming Environments: An experimental investigation through the group eye tracking (GET) paradigm Entertainment Computing 51 100714https://doi.org/10.1016/j.entcom.2024.100714
3. NC Anderson WF Bischof KE Laidlaw EF Risko A Kingstone 2013 Recurrence quantification analysis of eye movements Behav. Res. Methods 45 842 856 https://doi.org/10.3758/s13428-012-0299-5
4. MI Coco R Dale 2014 Cross-recurrence quantification analysis of categorical and continuous time series: an R package Front. Psychol. 5 510 https://doi.org/10.3389/fpsyg.2014.00510
5. L Conradt C List 2009 Group decisions in humans and animals: A survey Philosophical Transactions of the Royal Society B: Biological Sciences 364 1518 719 742 https://doi.org/10.1098/rstb.2008.0276
6. DA Dever MJ Amon H Vrzakova MD Wiedbusch EB Cloude R Azevedo 2022 Capturing sequences of learners' self-regulatory interactions with instructional material during game-based learning using auto-recurrence quantification analysis Front. Psychol. 13 813677https://doi.org/10.3389/fpsyg.2022.813677
7. M Dindar I Alikhani J Malmberg S Järvelä T Seppänen 2019 Examining shared monitoring in collaborative learning: A case of a recurrence quantification analysis approach Comput. Hum. Behav. 100 335 344 https://doi.org/10.1016/j.chb.2019.03.004
8. RV Donner 2011 Recurrence-based time series analysis by means of complex network methods International Journal of Bifurcation and Chaos 21 04 1019 1046 https://doi.org/10.1142/S0218127411029021
9. RV Donner J Heitzig JF Donges Y Zou N Marwan J Kurths 2011 The geometry of chaotic dynamics — a complex network perspective The European Physical Journal B 84 653 672 https://doi.org/10.1140/epjb/e2011-10899-1
10. RV Donner Y Zou JF Donges N Marwan J Kurths 2010 Recurrence networks—a novel paradigm for nonlinear time series analysis New J. Phys. 12 033025https://doi.org/10.1088/1367-2630/12/3/033025
11. Forsyth, D.R.: Group dynamics, 7th Edition. Cengage Learning Custom Publishing (2019)
12. Fusaroli, R., Tylén, K., Fusaroli, R., Tylén, K.: Investigating conversational dynamics: Interactive alignment, interpersonal synergy, and collective task performance. Cognitive Sci. **40**(1), 145–171 (2016) https://doi.org/10.1111/cogs.12251

13. P Grassberger I Procaccia 1983 Characterization of strange attractors Phys. Rev. Lett. 50 5 346 349 https://doi.org/10.1103/PhysRevLett.50.346
14. J Gudmundsson M Kreveld van B Speckmann 2007 Efficient detection of patterns in 2D trajectories of moving points GeoInformatica 11 2 195 215 https://doi.org/10.1007/s10707-006-0002-z
15. Jermann, P., Mullins, D., Nüssli, M.A., Dillenbourg, P.: Collaborative gaze footprints: Correlates of interaction quality. In: Spada, H., Stahl, G., Miyake, N.,Law, N. (Eds.), Connecting Computer-Supported Collaborative Learning to Policy and Practice: CSCL2011 Conference Proceedings. Volume I — Long Papers, pp. 184–191. International Society of the Learning Sciences, Hong Kong, China (2011)
16. Jermann, P., Nüssli, M.A.: Effects of sharing text selections on gaze cross-recurrence and interaction quality in a pair programming task. In: Proceedings of the ACM 2012 Conference on Computer Supported Cooperative Work, pp. 1125–1134 (2012) https://doi.org/10.1145/2145204.2145371
17. Knight, A.P., Kennedy, D.M., McComb, S.A.: Using recurrence analysis to examine group dynamics. Group Dynamics: Theory, Research, and Practice **20**(3), 223–241 (2016) https://psycnet.apa.org/doi/10.1037/gdn0000046
18. Lanata, A., Sebastiani, L., Di Gruttola, F., Di Modica, S., Scilingo, E.P., Greco, A.: Nonlinear analysis of eye-tracking information for motor imagery assessments. Frontiers in Neuroscience **13** (2020) https://doi.org/10.3389/fnins.2019.01431
19. D Lopez Perez P Tomalski A Radkowska H Ballieux DG Moore 2021 Efficiency of scanning and attention to faces in infancy independently predict language development in a multiethnic and bilingual sample of 2-year-olds First Lang. 41 2 218 239 https://doi.org/10.1177/0142723720966815
20. MM Louwerse R Dale EG Bard P Jeuniaux 2012 Behavior matching in multimodal communication is synchronized Cogn. Sci. 36 8 1404 1426 https://doi.org/10.1111/j.1551-6709.2012.01269.x
21. Mach, R., Schweitzer, F.: Multi-agent model of biological swarming. In: European Conference on Artificial Life, pp. 810–820. Berlin, Heidelberg: Springer Berlin Heidelberg (2011) https://doi.org/10.1007/978-3-540-39432-7_87
22. TK March SC Chapman RO Dendy 2005 Recurrence plot statistics and the effect of embedding Physica D 200 1–2 171 184 https://doi.org/10.1016/j.physd.2004.11.002
23. N Marwan JF Donges Y Zou RV Donner J Kurths 2009 Complex network approach for recurrence analysis of time series Phys. Lett. A 373 46 4246 4254 https://doi.org/10.1016/j.physleta.2009.09.042
24. N Marwan MC Romano M Thiel J Kurths 2007 Recurrence plots for the analysis of complex systems Phys. Rep. 438 5–6 237 329 https://doi.org/10.1016/j.physrep.2006.11.001
25. GM Mindlin R Gilmore 1992 Topological analysis and synthesis of chaotic time series Physica D 58 1–4 229 242 https://doi.org/10.1016/0167-2789(92)90111-Y
26. Moulder, R., Booth, B., Abitino, A., D'Mello, S.: Recurrence quantification analysis of eye gaze dynamics during team collaboration. In: LAK23, 13th International Learning Analytics and Knowledge Conference, pp. 430–440 (2023) https://doi.org/10.1145/3576050.3576113
27. Parrish, J. K., Hamner, W., Hamner, W.M. (Eds.): Animal groups in three dimensions: how species aggregate. Cambridge University Press (1997)
28. N Perony G Kerth F Schweitzer 2022 Data-driven modelling of group formation in the fission–fusion dynamics of Bechstein's bats J. R. Soc. Interface 19 190 20220170 https://doi.org/10.1098/rsif.2022.0170
29. Pietinen, S., Bednarik, R., Glotova, T., Tenhunen, V., Tukiainen, M.: A method to study visual attention aspects of collaboration: Eye-tracking pair programmers simultaneously. In: ETRA '08 Proceedings of the 2008 Symposium on Eye Tracking Research and Applications, pp. 39–42 (2008) https://doi.org/10.1145/1344471.1344480

30. Reddy, G.R., Eloy, L., Dickler, R., Reitman, J.G., Pugh, S.L., Foltz, P.W., ..., Hirshfield, L.: Synerg-eye-zing: Decoding nonlinear gaze dynamics underlying successful collaborations in co-located teams. In: Proceedings of the 25th International Conference on Multimodal Interaction, pp. 545–554 (2023) https://doi.org/10.1145/3577190.3614104
31. DC Richardson R Dale NZ Kirkham 2007 The art of conversation is coordination Psychol. Sci. 18 5 407 413 https://doi.org/10.1111/j.1467-9280.2007.01914.x
32. Richardson, T.O., Perony, N., Tessone, C.J., Bousquet, C.A., Manser, M.B., Schweitzer, F.: Dynamical coupling during collective animal motion. arXiv preprint arXiv:1311.1417 (2013) https://doi.org/10.48550/arXiv.1311.1417
33. B Schneider K Sharma S Cuendet G Zufferey P Dillenbourg R Pea 2018 Leveraging mobile eye-trackers to capture joint visual attention in co-located collaborative learning groups Int. J. Comput.-Support. Collab. Learn. 13 241 261 https://doi.org/10.1007/s11412-018-9281-2
34. B Schneider R Pea 2017 Real-time mutual gaze perception enhances collaborative learning and collaboration quality Educational Media and Technology Yearbook 40 99 125 https://doi.org/10.1007/s11412-013-9181-4
35. AJ Strang GJ Funke SM Russell AW Dukes MS Middendorf 2014 Physio-behavioral coupling in a cooperative team task: contributors and relations J. Exp. Psychol. Hum. Percept. Perform. 40 1 145 158
36. Tien, G., Atkins, M.S., Zheng, B.: Measuring gaze overlap on videos between multiple observers. In: ETRA ‘12: Proceedings of the Symposium on Eye Tracking Research and Applications, pp. 309–312 (2012) https://doi.org/10.1145/2168556.2168623
37. P Tomalski DL Pérez A Radkowska A Malinowska-Korczak 2022 Dyadic interactions during infant learning: Exploring infant-parent exchanges in experimental eye-tracking studies Infant Behav. Dev. 69 101780https://doi.org/10.1016/j.infbeh.2022.101780
38. CM Topaz AL Bertozzi 2004 Swarming patterns in a two-dimensional kinematic model for biological groups SIAM J. Appl. Math. 65 1 152 174 https://doi.org/10.1137/s0036139903437424
39. Vaidyanathan, P., Pelz, J., Alm, C., Shi, P., Haake, A.: Recurrence quantification analysis reveals eye-movement behavior differences between experts and novices. In: ETRA ’14 Proceedings of the Symposium on Eye Tracking Research and Applications, pp. 303–306 (2014) https://doi.org/10.1145/2578153.2578207
40. Veerabhadrappa, R., Hettiarachchi, I.T., Bhatti, A.: Using recurrence quantification analysis to quantify the physiological synchrony in dyadic ECG data. In: 2021 IEEE International Systems Conference (SysCon), pp. 1–8. IEEE (2021) https://doi.org/10.1109/SysCon48628.2021.9447059
41. Villamor, M.M., Rodrigo, M.M.T.: Predicting pair success in a pair programming eye tracking experiment using cross-recurrence quantification analysis. APSIPA Transactions on Signal and Information Processing **11**(1) (2022)
42. S Wallot P Mitkidis JJ McGraw A Roepstorff 2016 Beyond synchrony: Joint action in a complex production task reveals beneficial effects of decreased interpersonal synchrony PLoS ONE 11 12 e0168306https://doi.org/10.1371/journal.pone.0168306
43. S Wallot 2019 Multidimensional Cross-Recurrence Quantification Analysis (MdCRQA)–a method for quantifying correlation between multivariate time-series Multivar. Behav. Res. 54 2 173 191 https://doi.org/10.1080/00273171.2018.1512846
44. S Wallot A Roepstorff D Mønster 2016 Multidimensional Recurrence Quantification Analysis (MdRQA) for the analysis of multidimensional time-series: A software implementation in MATLAB and its application to group-level data in joint action Front. Psychol. 7 1835 https://doi.org/10.3389/fpsyg.2016.01835
45. S Wallot 2017 Recurrence quantification analysis of processes and products of discourse: A tutorial in R Discourse Process. 54 5–6 382 405 https://doi.org/10.1080/0163853X.2017.1297921

46. Webber, C.L., Ioana, C., & Marwan, N.: Recurrence plots and their quantifications: expanding horizons. Proceedings of the 6th International Symposium on Recurrence Plots, Grenoble, France. Springer Proceedings in Physics (2016) https://doi.org/10.1007/978-3-319-29922-8
47. Webber, C.L., Marwan, N. (Eds.): Recurrence Quantification Analysis: Theory and best practices. Springer Cham (2015) https://doi.org/10.1007/978-3-319-07155-8
48. JP Zbilut N Thomasson CL Webber 2002 Recurrence quantification analysis as a tool for nonlinear exploration of nonstationary cardiac signals Med. Eng. Phys. 24 1 53 60 https://doi.org/10.1016/S1350-4533(01)00112-6
49. JP Zbilut CL Webber Jr 2007 Recurrence quantification analysis: Introduction and historical context International Journal of Bifurcation and Chaos 17 10 3477 3481 https://doi.org/10.1142/S0218127407019238