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Capturing moment-to-moment changes in multivariate human experience

Naomi M. P. De Ruiter,* Steffie Van Der Steen,* Ruud J. R. Den Hartigh, and Paul L. C. Van Geert

Abstract

In this article, we aim to shed light on a technique to study intra-individual variability that spans the time frame of seconds and minutes, i.e., micro-level development. This form of variability is omnipresent in behavioural development and processes of human experience, yet is often ignored in empirical studies, given a lack of proper analysis tools. The current article illustrates that a clustering technique called Kohonen's Self-Organizing Maps (SOM), which is widely used in fields outside of psychology, is an accessible technique that can be used to capture intra-individual variability of multivariate data. We illustrate this technique with a case study involving self-experience in the context of a parent–adolescent interaction. We show that, with techniques such as SOM, it is possible to reveal how multiple components of an intra-individual process (the adolescent's self-affect and autonomy) are non-linearly connected across time, and how these relationships transition in accordance with a changing contextual factor (parental connectedness) during a single interaction. We aim to inspire researchers to adopt this technique and explore the intra-individual variability of more developmental processes, across a variety of domains, as deciphering such micro-level processes is crucial for understanding the nature of psychological and behavioural development.

Keywords

cluster analysis, intra-individual variability, Kohonen's Self-Organizing Maps, micro-level development, person-oriented approach, process approach, self-experience

Behavioural and psychological changes occur on various time scales (Ram & Gerstorf, 2009; Siegler & Crowley, 1991; Van Geert, 2011). At the macro level, structured and recurring patterns are revealed, such as skills or trait-like properties, that develop across a relatively large time scale, ranging from weeks to years (Lewis, 2002). Alongside the macro level, behavioural and psychological changes occur on the micro level, in the form of sequences of actions and experiences (Fischer & Bidell, 2006; Lichtwarck-Aschoff, Van Geert, Bosma, & Kunnen, 2008). These microgenetic processes refer to the moment-to-moment changes in human experience, and the moment-to-moment changes in factors that influence these experiences (Granic & Patterson, 2006; Lewis, 2002; Siegler & Crowley, 1991), reflected by a variable real-time developmental trajectory (Lewis, 2002; Lichtwarck-Aschoff et al., 2008). These processes are by definition *intra-individual* processes, involving intra-individual variability (Van Dijk & van Geert, 2007).

While researchers often (implicitly) assume that information regarding intra-individual processes can be deduced from analyses of inter-individual variability (Van Geert, 2011), this is not justified, unless the ergodicity principle holds (Molenaar, 2004; Molenaar & Campbell, 2009; Salvatore & Valsiner, 2008). A process is "ergodic" when a structural analysis of inter-individual variability yields the same results as a structural analysis of intra-individual variability, and when the process is stationary (Flyvbjerg, 2006; Molenaar, 2004; Molenaar & Campbell, 2009). Strikingly, it has been found that most psychological processes are not ergodic (Denissen, Penke, Schmitt, & Van Aken, 2008; Molenaar, 2004; Tennen, Affleck, Armeli, & Carney, 2000). As a result, methodological tools that are capable of capturing intra-individual variability should be used when studying intra-individual processes. However, in the domain of psychology, such tools are not common (Ram & Gerstorf, 2009; Van Geert & Van Dijk, 2002).

In the current article, we describe a dynamic clustering technique that can be used to understand micro-level intra-individual processes: Kohonen's Self-Organizing Maps (SOM; Kohonen, 1982). We illustrate the utility of this technique with a case study involving an adolescent's expression of self-directed emotions and autonomous actions during a parent–child interaction. While macro-level parental connectedness positively influences the development of adolescent emotional functioning (e.g., across 5 years; Boutelle, Eisenberg, Gregory, & Neumark-Sztainer, 2009), it is, as yet, unknown how this relationship unfolds *during* parent–child interactions.

It can be expected that the relationship between variables on the micro-level will be non-linear (Nowak & Vallacher, 1998), such that the relationships between parental connectedness and adolescent expressions of self-affect and autonomy (and between these expressions themselves) may change across the interaction.

University of Groningen, The Netherlands

*These authors contributed equally to the work and should both be considered first author.

Corresponding author:
Naomi M. P. De Ruiter, University of Groningen, Grote Kruisstraat 1/2, Groningen 9712 TS, The Netherlands.
Email: n.m.p.de.ruiter-wilcox@rug.nl

Moreover, these variables likely develop in a non-linear fashion across real-time, such that the shape of change itself may change across time, from monotonic change, to variable periods of continuities and discontinuities, for example (Van Dijk & Van Geert, 2007). Such information regarding possible *non-linear relationships* between these micro-level variables and their *non-linear changes across time* is necessary, firstly, in order to understand the real-time building blocks for macro-level findings. Indeed, studies have shown that long-term patterns of change between parent and child are grounded in real-time interactions (Hollenstein, Granic, Stoolmiller, & Snyder, 2004; Lichtwarck-Aschoff, Hasselman, Cox, Pepler, & Granic, 2012), making it necessary to accompany macro-level developmental studies with micro-level studies. Secondly, information regarding micro-level processes is valuable for theoretical purposes. An in-depth understanding of the *nature* of adolescent self-expression and parental connectedness during interactions can only be achieved by empirically investigating idiosyncratic cases of this relationship. Hence, with intra-individual data, it is possible to generalize from empirical measurements to meta-theories or to more specific theory development (Flyvbjerg, 2006; Ruddin, 2006), rather than generalizing from empirical data to a description of the population (Lee & Baskerville, 2003).

Although dynamical time-series techniques exist that allow for either the study of intra-individual variability over time (Ram & Gerstorf, 2009; Tan, Shiyko, Li, Li, & Dierker, 2012), or for the study of the relationship between intra-individual variability and external variables (Shiyko & Ram, 2011), the technique that we will demonstrate (SOM) allows for the investigation of both of these characteristics simultaneously: non-linear development of relations between multivariate data. As such, SOM offers opportunities for studying intra-individual variability of multiple components embedded in a constantly changing context.

Capturing the structure of intra-individual micro-level data: Kohonen's self-organizing maps

Kohonen's Self-Organizing Maps is commonly used as a powerful tool for the visualization of complex data (Kamimura, 2012) in fields such as engineering, medicine, and economics, but not in psychology. Due to its ability to capture non-linear temporal changes within multiple variables across time (i.e., not just monotonic increases or decreases), as well as changes in the relationship between these variables across time (i.e., not just linear associations between variables), this technique is suitable for the study of psychological processes typically characterized by these features.

The SOM does not predict (patterns in) a dependent variable based on a combination of independent variables. Rather, the SOM maps the spatial and temporal emergence of (unknown) structure in multivariate time-serial data by means of an "unsupervised learning algorithm." This means that the target output is discovered in a recursive process by means of the input data, and hence not specified by the researcher beforehand. The SOM learning process works by recursively comparing pairs of vectors: An empirical vector that represents the input data and a model vector (from the developing map). The model vector is continuously calculated and updated based on the value of the empirical vector and its position on the time series. If the vectors differ, the model vector is altered slightly so that dissimilarity is reduced. This is repeated multiple times, where at each step an empirical vector is presented to a new

Table 1. Characterization of four clusters of self-experience during the parent–adolescent interaction.

Component	Test value			
A (20% window)				
	Cluster 1 (12.0%)	Cluster 2 (39.0%)	Cluster 3 (34.1%)	Cluster 4 (14.9%)
Self-affect	25.69	−5.14	−5.18	−9.52
Autonomy	18.91	−12.35	11.68	−15.95
B (30% window)				
	Cluster 1 (13.2%)	Cluster 2 (53.4%)	Cluster 3 (27.7%)	Cluster 4 (5.7%)
Self-affect	26.16	−12.39	−2.42	−6.79
Autonomy	20.64	−13.84	8.11	−15.94

Note. The percentages indicate the percentage of temporal data characterized by each cluster. For more information about the content and interpretation of this table, see Results section. For comparison, this table shows two outcomes, one with smoothed data using a window of 20% (A), and one with a window of 30% (B). The test values (indicating the weight of the variable in each cluster) change slightly when using a different smoothing window, but the relative changes (positive/negative) remain the same.

model vector, until the map fully represents the structure of the empirical data. Through this process, the accuracy of the map continuously improves with each iteration as it "learns" to represent the structure of the data. When the learning process is finished, the final map optimally represents the organization of the data across time (Kohonen, 1982; Lagus et al., 1996). For more specifics regarding the SOM algorithm and the specific learning rules, see Kohonen (1982).

The resulting map reveals the organization of the data as a new higher-order dimension, represented by a number of clusters. Importantly, the SOM keeps track of the time point that each data point falls into the various clusters (Ultsch, 1999). Therefore, the resulting clusters are able to keep the "topological structure" (i.e., the relationship between data points *over time*) intact, which is vital for capturing the non-linear temporal patterning of intra-individual data (De Ruiter, Den Hartigh, Cox, Van Geert, & Kunnen, 2015; Ram & Gerstorf, 2009; Tan, Shiyko, Li, Li, & Dierker, 2012). The map is expressed as a small set of qualitatively different clusters that emphasize the salient features of variables and their relationships (Table 1), as well how these features show temporal recurrence (see Figure 1). This means that each variable can contribute to multiple clusters, that is, each cluster represents a different *relationship* between the *same* variables. Thus, rather than collapsing the "time" component of the data and determining the statistical similarity between the various variables, the SOM determines the *dynamic* correspondence between variables (Skific & Francis, 2012).

There are other dynamic methods available that also consider dynamical aspects of (usually longitudinal) data, such as variability and the temporal organization of the behavioural process at the long term (e.g., Boker & Nesselroade, 2002; Hu, Boker, Neale, & Klump, 2014; Molenaar, 1985; Oravecz, Tuerlinckx, & Vandekerckhove, 2011), and which are also often applied to within-person constructs varying from day to day, such as affective processes or (emotion) regulation (Boker & Nesselroade, 2002; Oravecz et al., 2011). These techniques are based on specific theories that specify the relations between variables, expressed in the form of differential

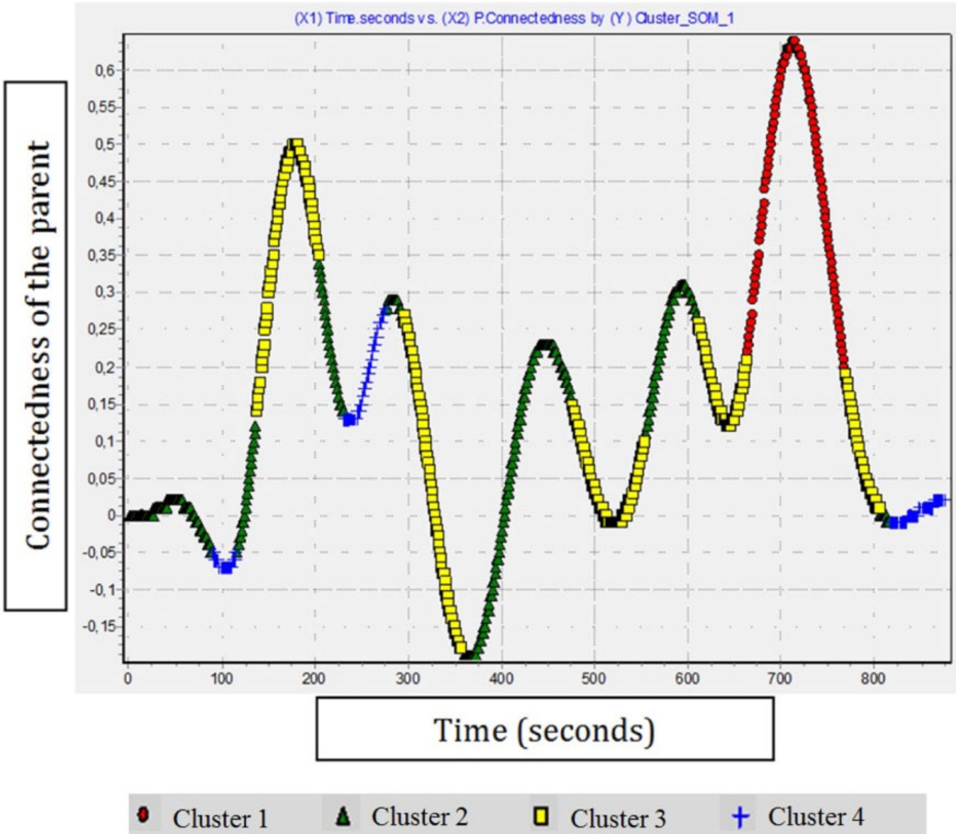

Figure 1. Temporal emergence of clusters based on multivariate time series. For more information about the content and interpretation of this figure, see Results section. The Y-axis represents the connectedness of the parent toward the adolescent (higher numbers correspond to more connectedness), and the X-axis represents the time (seconds). The legend indicates the four different clusters that describe the intra-individual Self-affect and Autonomy data of the adolescent over time (see Table 1).

equations. These equations are then fitted to the data by means of parameter estimation. Kohonen's SOM, however, enables researchers to explore structure in intra-individual variability when there is no theory about the specific relations between variables (e.g., parent and child variables). In this sense, SOM is data-driven, and can be used for exploratory analyses. Its results can be interpreted from the perspective of complex dynamic systems (CDS), which is a meta-theory that assumes that phenomena of all kinds (such as dyadic interactions, or self-experiential patterns) can best be conceptualized as higher-order structures that self-organize out of non-linear interactions between lower-level components across time. The SOM is thus particularly useful when researchers are interested in studying the (unknown) dynamics and underlying structure of their data, and when there is no theory available that is specific enough to imply differential equations or formal decision rules to their data (which is often the case for micro-level data).

The SOM also differs from other *clustering techniques* that are used for time-serial data, such as hierarchical agglomerative clustering (Borgen & Barnett, 1987), which tend to identify groups of similar time series. In contrast to this, the SOM identifies groups of *interactions between* the time series that occur across time. Hence, the clusters acquired by SOM form their own (higher-order) time series (this is further described in the case-study example in what follows). Furthermore, the SOM has been found to be superior to clustering techniques such hierarchical clustering in its ability to classify datasets correctly and without previous information on the data (Ultsch & Vetter, 1994), as well as for being robust against noise (Zhang & Fang, 2012).

Data requirements for SOM

Time-serial input data for Kohonen's SOM can be either discrete or continuous (Allende, Moreno, Rogel, & Salas, 2004). When a researcher wishes to conduct the SOM on multivariate data, a value is required for all variables for each measurement point (Germano, 1999). This can be achieved in two ways, either by measuring the variables across the same time-interval so that all time series are parallel, or, if there is a difference in time-intervals, by conducting a smoothing technique on the various time series, so that a score is created for all measures at each measurement point (Fu, Chung, Ng & Luk, 2001; for an example see our case study). Furthermore, all variables from the dataset should either be on the same scale, or normalized so that no variables artificially dominate the clustering process (Taner, 1997), where the z-score normalization is recommended (Parshutin, 2007).

Finally, time series must contain enough units so that the essential characteristics of the process can be captured. Relatively long time series will allow for a more specific and detailed picture of the temporal structure, while relatively short time series will result in a more global picture. To date, the range with respect to the length of time series used for SOM is notably large, ranging from 9 or 15 points to hundreds of data points (Fu et al., 2001; Parshutin, 2007).

Conducting the SOM analysis

The SOM technique is an accessible and user-friendly technique that can be conducted using statistical packages in, for example, Matlab (Vesanto, Himberg, Alhoniemi, & Parhankangas, 2000), R (Wehrens & Buydens, 2007), Orange (Demšar et al., 2013) or Tanagra (Rakotomalala, 2003). We will proceed with the case-study in which we demonstrate the SOM technique, using Tanagra software.[1]

For a SOM analysis, the number of clusters is established by the researcher. While some researchers may consider this a limitation, it is important to note that the original patterns found in the data are not affected by the number of clusters chosen, as the topological structure will always be maintained (Kohonen, 1982). Moreover, small differences in the chosen number of clusters do not influence the results of subsequent analyses (Skific, Francis, & Cassano, 2009). Although there are no strict guidelines for the number of clusters, an advantage of using the SOM technique is that multivariate data can be portrayed in a low-dimensional space, that is, characterized by a *small* number of clusters. The exact amount of clusters chosen ultimately depends on the dataset and research aim. For datasets that contain a small number of variables, the number of clusters should not far exceed the number of variables (Ultsch, 1999). Regarding the aim, a smaller number of clusters provides a more global picture, and a larger number of clusters provides a more specific description (Skific & Francis, 2012).

Additionally, a number of steps can be followed to determine the ideal number of clusters and their validity (see Results): (1) Kohonen's SOM indicates the amount of data that each cluster characterizes (e.g., see Table 1). This is useful for identifying the presence of redundant clusters (indicating the need for a smaller number of clusters), which can be seen if a cluster is characterized by a disproportionately small amount of the data. (2) We advise researchers to assess whether each variable contributes sufficiently to each cluster. This can be done by calculating the Test Values (TV, see Table 1), which can be obtained in Tanagra (see Supplementary material for instructions). The TV compares the mean of the variable across the whole dataset (e.g., the mean level of the adolescent's self-affect) to the mean of that variable in this specific cluster (e.g., the mean level of the adolescent's self-affect within a particular cluster). The TV criterion asymptotically follows a Gaussian distribution. Absolute values greater than 2 signal a probable significant effect ($p < .05$), which means that the value of the variable in a specific cluster would be significantly different from its value during the rest of the interaction, and that the variable has sufficient weight in each cluster (Rakotomalala, 2003). Moreover, a TV with a higher absolute value indicates a higher weight in the respective cluster, and the sign of the TV indicates whether the variable is characterized as positive or negative in each specific cluster. The TV thereby also characterizes the nature of the cluster. Given that the above two criteria are met, the quality of the cluster map can then be assessed by (3) the amount of explained variance provided by the clusters. Next, in order to determine whether the clusters provide meaningful information regarding the underlying variability across time, a number of measures can be taken. (4) A visual analysis of the temporal structure of the clusters provides information on whether the clusters seem to be randomly scattered across the time series, or if they seem to indicate a pattern. (5) Researchers can then check whether the resulting pattern is not based on chance, by conducting the same SOM analysis on the same time series after it has been shuffled, and visually comparing the two. Finally, (6) the above assessments should be made for multiple numbers of clusters, to determine which number best meets the above criteria.

Case-study example: Mapping intra-individual changes in self-experience

In this case study, SOM is used to understand the temporal structure of an adolescent's micro-level expressions of self-directed emotions and autonomous actions across a parent–adolescent interaction, as well as how this structure is interconnected with micro-level changes of parental expression of connectedness. Data for this case study is part of a larger research project (De Ruiter, 2015). Specifically, we use the moment-to-moment changes in the adolescent's self-expressions as input data for the SOM, and examine the simultaneous changes that occur in the parents' expression of connectedness toward the adolescent.[2]

Method

Participants

We used observational data for one parent–adolescent dyad (female parent, aged: 49.5 years; male child, aged 12.3 years) from a larger sample (De Ruiter, 2015). The parent–adolescent dyads responded to recruitment flyers handed out in local community centres and schools. The participants are Dutch, have no indication of clinical diagnoses, and are of average socioeconomic status. Participation was rewarded with a €5 gift voucher. The study was approved by the Ethics Committee of the authors' university.

Procedure

The parent–adolescent interaction was captured on film in the participants' home environment and coded in a time-serial manner afterward, based on an a priori coding system (see Supplementary material). The researcher gave the dyad two slightly positive topics to discuss (e.g., "If you could travel through time, to which time period would you travel?"), and participants chose a relevant conflict topic ("cleaning up your room"). Topics were followed in a positive-conflict-positive order, meant to elicit a wide range of self- and other-directed experiences. The interaction lasted 14.6 minutes in total.

Measures

The observational videos were coded with The Observer XT 10.5. The coding system allows for the measurement of affect and autonomy-related behaviour of parents and children during interactions. In the current case study, measures of parental connectedness, adolescent self-affect (Epstein & Morling, 1995; Scheff & Fearon, 2004), and adolescent autonomy (Allen, Hauser, Bell, & O'Connor, 1994; Deci & Ryan, 1991) were included. The coding scheme was previously used in (De Ruiter, Den Hartigh, Cox, Van Geert, & Kunnen, 2015), where further theoretical description regarding the measurement of these variables can be found. Coding was event-based, such that a score was given for each relevant verbal/non-verbal expression across the interaction. Observers were extensively trained until at least 75% agreement was reached before coding commenced. Average between-observer agreement for coders who independently coded 10% of the total data was 85.5% ($k = 0.77$).

Adolescent self-affect was scored on an ordinal scale of −3 to 3 (where −3 = shame, −2 = sadness, −1 embarrassment, 1 = self-interest, 2 = self-humour, 3 = pride). A score was given for each moment that self-affect was expressed, based on the adolescent's facial expressions (e.g., eyes cast down), body posture (e.g., shoulder and head down), intonation (e.g., quiet voice), and verbalizations (e.g., "I'll never learn").

Adolescent autonomy was scored on an ordinal scale of −2 to 3[3] (where −2 = submission, −1 = dependence, 1 = expression of attitude/idea, 2 = agency, 3 = self-assertion). A score was given for each moment that autonomy-related behaviour was expressed, based on the adolescent's actions (e.g., interrupts parent) and verbalizations (e.g., "no, you're wrong").

Parental connectedness was scored on an ordinal scale of −3 to 3 (where −3 = contempt, −2 = anger, −1 = disinterest, 1 = interest, 2 = joy, 3 = affection). A score was given for each moment that connectedness was expressed, based on facial expressions (e.g., eye contact and warm smile), movements (e.g., hugging adolescent), intonation (e.g., raised voice), and verbalizations (e.g., "I like that we have this time together").

Analyses

The time series of Self-affect, Autonomy and Connectedness (875 data points) were smoothed using a LOESS technique in preparation for Kohonen's SOM. LOESS is a local-regression technique that smooths time-serial data in a non-linear manner within a small window (e.g., 20% of the total data), which then continuously moves from one point to the following. The values within the moving window are weighted (least squares) on the measure at the centre of the window, in such a way that observations closer to the centre of the window have more impact on the shape of the curve at that particular point. This is helpful for time series that contain missing data or unequal intervals, since a new score is estimated for each particular moment based on the neighbouring scores. The Loess curve is fitted to follow the general trends of the data, which ensures that the temporal structure is protected. Jacoby (2000) notes that the window should be selected on a case-by-case basis (see Cleveland & Devlin, 1988, for a formalized account). In the current case study, a window of 20% was chosen. This choice reflects our view of what the essential variability in our specific dataset is and what variability can be safely disregarded (Van Dijk & van Geert, 2007). In our dataset, a score of zero was given as default when no meaningful expressions of self-experience and connectedness were detected, resulting in some second-to-second variability that does not reflect a true "drop" in the participants' experience. A window of 20% was sufficient to filter out this artefact of the coding process. The data was then normalized using z scores.

The SOM technique was then conducted. The resulting map consists of clusters identified by the SOM (Table 1). Because the relationships between the variables are tracked across time, the map can be expressed as a new higher-order time series, revealing which cluster is expressed at each moment across the original time series (e.g., t_i to t_{i+n} = Cluster 1; t_{i+n} to $t_{(i+n)+n}$ = Cluster 2, etc.). To see how the variability in Autonomy and Self-affect corresponded to temporal changes in the external variable parental Connectedness, the higher-order time series was projected as various colours/shapes onto the time series of parental Connectedness in a scatter plot (Figure 1). The clusters are characterized in terms of how dominant each variable was in the formation of that cluster, based on the Test Values (TV) obtained in Tanagra (see Conducting the SOM analysis, above).

Results

The SOM analysis was conducted for four clusters. These clusters explained 80% of the variance in the smoothed intra-individual data.[4] The characteristics of the four clusters are presented in Table 1, which includes the percentage of time that each cluster was active during the interaction, and the TVs for each input variable. Table 1 shows that the data is sufficiently distributed across the four clusters, and that all contributing variables have a TV ≥ 2. Figure 1 (shown as originally depicted by the analysis output in Tanagra) shows the temporal relationship between the time series of the adolescent's self-experiential clusters (transitions between the various colours/shapes) and the changing level of parental Connectedness (values on the y-axis).

Defining the ideal number of clusters and their validity

While more clusters explained more variance (e.g., five clusters explained 84% of the variance), the Test Value (TV) for Self-affect was −0.09 for one of the clusters, indicating an insufficient contribution to that cluster. Moreover, the temporal pattern of five clusters was comparable to that of four clusters, but with one of the clusters from the four-solution outcome being roughly differentiated into two separate clusters. While smaller numbers of clusters fit the data based on the criteria of data distribution and TVs, fewer than four clusters resulted in a relatively large drop in explained variance (three clusters explained 73% of the variance, and two clusters explained 51% of the variance). A four-cluster solution was therefore deemed to best represent the data.

In order to test the validity of the resulting clusters, the SOM analysis was conducted with, firstly, a different level of smoothing (i.e., 30% window). The results remained largely similar (83% explained variance), shown in Table 1. This indicates that the SOM analysis is not overly sensitive to changes in the amount of temporal variability. While some changes are to be expected, as increasing the window size for smoothing means that the temporal variability is slightly dampened, the general characterization of the clusters and the relative differences remain similar. This corresponds with the general finding that SOM is relatively robust against noise (Zhang & Fang, 2012).

The SOM analysis was, secondly, conducted multiple times after 15 permutations of the raw data, where blocks of 10–20 data points (i.e., seconds) were shuffled randomly across the time series. This simulated a time series without any meaningful underlying temporal structure, but where measurement points within windows of 10–20s are potentially related (as might be possible in psychological data). Four clusters (the number used for the original analysis) proved to be a poor fit for the shuffled time series. This can be seen based on the first two criteria mentioned in the section *Capturing the structure of intra-individual micro-level*

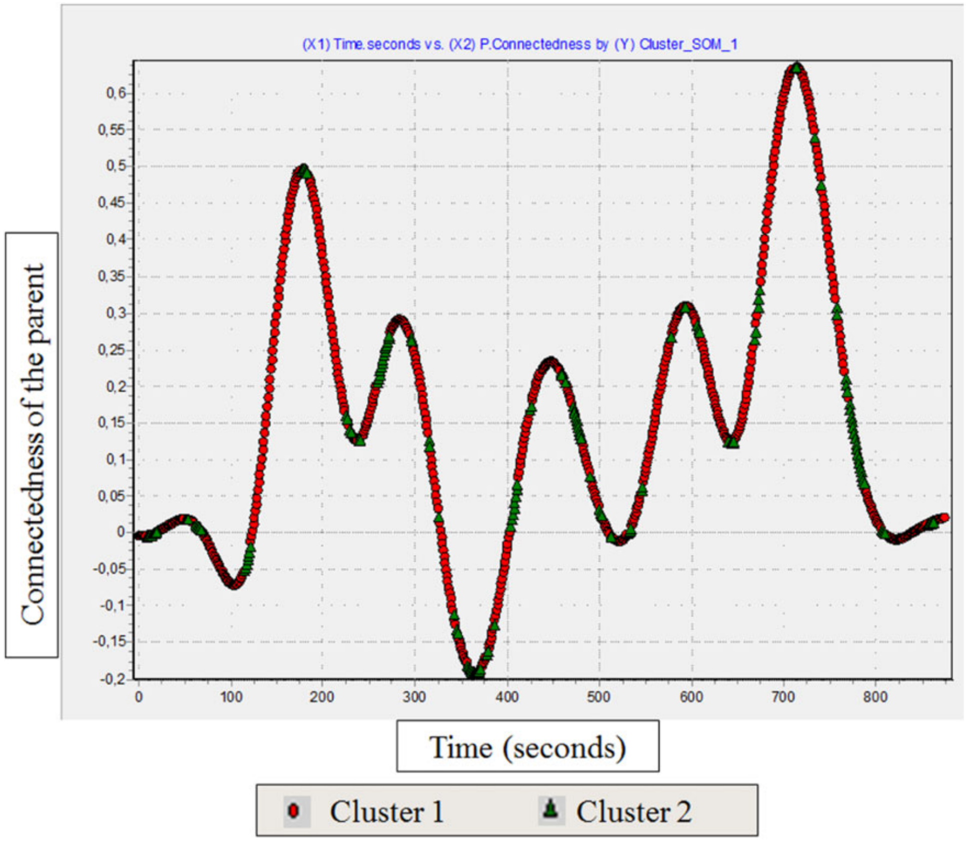

Figure 2. Temporal emergence of clusters based on shuffled multivariate time series. The Y-axis represents the connectedness of the parent toward the adolescent (higher numbers correspond to more connectedness), and the X-axis represents the time (seconds). The legend indicates the two different clusters that describe the shuffled intra-individual Self-affect and Autonomy data of the adolescent. The temporal portrayal of the clusters based on the shuffled time series shows a lack of structure.

data: Kohonen's Self-Organizing Maps, where we discussed how to choose the optimal number of clusters. Firstly, the mean distribution of data points across the four clusters was highly uneven: Cluster 1: 7.4% (SD = 0.00), Cluster 2: 74.11% (SD = 0.49), Cluster 3: 18.88% (SD = 1.91), Cluster 4: 0.06% (SD = 0.23), with Cluster 4 proving to be completely redundant. Secondly, the TVs were lower than 2 for one or more variables in Cluster 1 and Cluster 4, which signals a statistically insignificant contribution of a specific variable to the cluster. Thus, while the four clusters explained a large amount of the variance in the data (average explained variance = 87.07%, SD = 3.33), this value is not valid, given that the cluster-choice of four failed to meet the above criteria. This illustrates why it is important to consider other criteria than just the explained variance. Similar results (i.e., an uneven distribution of data points across the clusters, and insignificant TVs) were also found for a solution with three clusters on the shuffled data.

Based on the distribution of data points and the TVs, the SOM revealed that a map of two clusters best fit the *shuffled* data, with a much lower average explained variance of 42% (SD = 1.00). Importantly, while the SOM analysis with two clusters meets the above criteria for fitting the data, the temporal portrayal of the clusters across the shuffled time series showed a lack of structure (see Figure 2), demonstrating that meaningful *temporal* structure of the current data is only found by SOM when it is indeed present, and not when it is absent.

Interpreting the clusters

With regard to the clusters that were revealed based on the *observed* data, Cluster 1 characterized 105 data points (12.0% of the interaction). This cluster only occurred at one point during the time series, specifically, during the largest peak in parental Connectedness (see Figure 1). Table 1 shows that Cluster 1 is characterized by the most positive adolescent self-experience compared to the other clusters, with TV = 25.69 for Self-affect and TV = 18.91 for Autonomy.

Cluster 2 was the most dominant cluster, characterizing 341 data points (39.0% of the total interaction). Figure 1 shows that this cluster repeatedly occurred during the time series, and that it often corresponded with a temporal *increase* in parental connectedness. Table 1 reveals that Cluster 2 is characterized by a moderately negative level of Self-affect (TV = −5.14) and a highly negative level of Autonomy (TV = −12.35).

Cluster 3 characterizes 298 data points (34.1% of the total interaction). Figure 1 shows that Cluster 3 also repeatedly occurred, and that it often co-occurred with a temporal *drop* in parental connectedness. Table 1 shows that this cluster is characterized by moderately negative Self-affect (TV = −5.18), in combination with highly positive Autonomy (TV = 11.68).

Finally, Cluster 4 characterizes 130 data points (14.9% of the total interaction). This cluster tended to occur for shorter periods, namely, when parental connectedness dipped (see Figure 1).

Table 1 reveals that self-experience was the most negative in this cluster compared to the others (TV $= -9.52$ for Self-affect and TV $= -15.95$ for Autonomy).

Discussion

In this article, we illustrated the utility of a technique that can be used to understand micro-level intra-individual processes: Kohonen's Self-Organizing Maps (SOM; Kohonen, 1982). We applied this technique to the study of an adolescent's expression of self-directed affect and autonomous actions during a parent–child interaction. Results based on the SOM analysis showed that there are distinct ways (i.e., clusters) in which the adolescent experienced himself emotionally (Self-affect) and behaviourally (Autonomy) across the parent–child interaction. Thus, the relationship between these variables demonstrated non-stationarity across the interaction. Note that although Kohonen's SOM does not assume that the relationships between the variables remain constant during the interaction (indicated by the interchanging clusters), the relationship between the input variables is assumed to be constant within a specific cluster.

Two of these clusters were the most characteristic forms of self-experience for this adolescent (as indicated by a relatively high percentage of occurrence), namely moderately negative self-affect combined with either highly autonomous behaviour (Cluster 3), or highly heteronomous behaviour (Cluster 2), experienced interchangeably over time. Whereas an analysis of the linear relationship between the adolescent's expressions of self-affect and his autonomous actions would reveal a positive correlation ($r = 0.63$, based on the case-study data), the SOM analysis revealed that there is a non-linear relationship between the adolescent's self-experiential measures, where the relationship between the two changed systematically across the time span of an interaction.

As studies tend to focus on between-individual relationships at the trait level, these results can be used for theory-development at the within-individual level. This case study illustrates that individuals can be characterized by multiple, seemingly contradictory, ways of experiencing the self *across a single interaction* (Cluster 1 was "positive" and Cluster 4 was "negative") and at *the same time* (Cluster 3 was characterized by negative Self-affect as well as positive Autonomy). This is in contrast with findings that point toward a simple positive within-individual relationship between these processes in daily life (e.g., Heppner et al., 2008).

In addition, the SOM analysis revealed that the temporal relationship between parental Connectedness and the child's emotional and behavioural self-experiences is *not* linear. While a positive relationship was seen for Clusters 1 and 4 (a large peak in Connectedness corresponded with "positive" self-experience, and clear dips in Connectedness corresponded to "negative" self-experience), a negative relationship occurred for Cluster 3 (a temporal drop in parental Connectedness corresponded with "mixed" adolescent self-experiences), and a temporal increase in parental Connectedness corresponded with relatively negative adolescent self-experience (Cluster 2).[5] This illustrates a more complex picture of parent–child interaction than the linear relationship that is reported in the literature (higher parental connectedness traditionally corresponds with more positive self-affect and autonomy in children, e.g., Ryan & Deci, 2000), and which is found for the present data when a linear method is applied (the correlation between parental Connectedness and child Autonomy is $r = .53$, and $r = .67$ for Self-affect). The flexible transitioning between patterns seen in the current case study is relevant in light of similar micro-studies on parent–child conflicts in adolescence, where rigid patterns (and especially a lack of variability) in interactions (clearly not the case in the present case study) are associated with problematic parent–child relationships (e.g., Hollenstein et al., 2004).

The utility of this case study's results lies, first, in its use for hypothesis-building regarding within-individual processes of self-experience in the context of parent–child interaction. Second, the strength of our $n = 1$ idiosyncratic results is in their generalization and contribution to theory development regarding the *nature* of micro-level processes in general. Our findings show that parent–child interactions reveal more than simple cause–effect relationships. Firstly, patterns of self-experience emerged (i.e., self-affect and autonomy clusters), evidenced by the fact that specific self-affect–autonomy associations *re-occurred* across the interaction. This is in accordance with the complex dynamic systems perspective (i.e., a meta-theory) of a system (i.e., the child's self-experience) consisting of interconnected elements that iteratively interact, producing higher-order properties that can demonstrate multi-stability (Van Geert & Fischer, 2009). Second, the results reveal that the temporal structure of the child's self-experience is also continuously interacting with the immediate environment—here, the parent's expression of connectedness. The adolescent's real-time process of self-experience depends on his own intrinsic dynamic of self-experiential elements, as well as the interaction between this process and his experience of the parent's emotional expression toward him (Vallacher, Van Geert, & Nowak, 2015).

Limitations and future perspectives

While the current analysis focuses on conducting the SOM for $n = 1$ in order to illustrate how intra-individual temporal structure can be captured, the SOM can be applied to a larger sample. This can be done by clustering across the larger sample, where multiple individual time series are treated as if they are one-time series for each measure. This would result in one set of clusters that represent the entire sample's collective temporal structure. This approach, while possible, would assume that all individuals within the sample have a homogenous temporal structure. Alternatively, the idiosyncratic nature of the time series can be preserved if the SOM analysis is conducted on an intra-individual basis, but for multiple participants. This would result in a separate set of clusters for each individual, upon which follow-up analyses can be done to determine similarities or differences across the individuals.

While demonstrations of these follow-up analyses (for both case studies and larger samples) goes beyond the scope of the current article, in brief, the new higher-order time series of the SOM can be used as input data for subsequent analyses. With a Markov Chain method (Kapland, 2008), it would be possible to predict the temporal ordering of the intra-individual clusters. Using State Space Grid methodology (Hollenstein, 2012; Lewis, Lamey, & Douglas, 1999), the moment-to-moment changes between the within-individual cluster transitions and the changes in the corresponding parental behaviour could be quantified. Hierarchical clustering techniques could be applied to a larger dataset to investigate between-individual similarities in trajectories (Borgen & Barnett, 1987). Furthermore, a SOM analysis could be repeated across multiple waves of real-time data to investigate the long-term stability of the clusters.

Finally, we want to emphasize that this is, to the best of our knowledge, the first application of Kohonen's SOM to the study of intra-individual changes in behaviour. To further strengthen the value of this technique for the social sciences and to create a consistent research base, more applications of this technique are encouraged.

Conclusion

In this article, we highlighted the importance of capturing intra-individual variability in studying micro-genetic processes of human experience. We emphasized that, in order to capture meaningful intra-individual variability, it is necessary to investigate the temporal unfolding of the data, and to do so on a within-individual basis (cf. Bergman & Vargha, 2013; Ram & Gerstorf, 2009; Van Geert & Van Dijk, 2002). As human experience changes continuously, it is of utmost importance to explore both non-linear changes in direction (i.e., decreases as well as increases) as well as in the relationships between multiple variables (i.e., positive as well as negative relationships between variables).

This article demonstrates that the SOM technique is well suited to the aim of capturing non-linear intra-individual changes and relationships between variables in multivariate data. Using the SOM, we could acquire a picture of how multiple interconnected components of an intra-individual process self-organize across time, revealing non-linear relationships between variables, and how these relationships transition in accordance with a changing contextual factor.

Finally, we aim to encourage researchers to explore the nature of developmental processes, across a variety of domains, by examining the intra-individual variability of these processes. Given that dynamic clustering techniques, Kohonen's SOM in particular, are available in various software packages, researchers may take advantage of this to aid our understanding of (individual) behavioural and psychological development.

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Supplemental material

Supplementary material for this article is available online.

Notes

1. Readers who are interested in learning how the analysis can be conducted in Tanagra can find the dataset, as well as step-by-step instructions, in the Supplementary material.
2. While we chose to use only the adolescent's self-expressions as input data for the SOM analysis, it is possible to include parental measures, for example, as input data as well, assuming that there is a theoretical reason for doing so.
3. The autonomy scale is not symmetrical as there were more categories for autonomous behaviour than for heteronomous behaviour.
4. Although we worked with the smoothed data (see Analysis section), the clusters explained a comparable portion of the variance when clustering the unsmoothed data (namely, 78%).
5. While the patterns of Self-affect and Autonomy are discussed with regard to how they correspond with changes in parental connectedness, we do not intend to say that parental connectedness causes variations in the adolescent's self-affect and autonomy, merely that these variations co-occur with changes in parental connectedness.

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