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Original Article

Inspecting Gradual and Abrupt Changes in Emotion Dynamics With the Time-Varying Change Point Autoregressive Model

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Abstract: Recent studies have shown that emotion dynamics such as inertia (i.e., autocorrelation) can change over time. Importantly, current methods can only detect either gradual or abrupt changes in inertia. This means that researchers have to choose a priori whether they expect the change in inertia to be gradual or abrupt. This will leave researchers in the dark regarding when and how the change in inertia occurred. Therefore in this article, we use a new model: the time-varying change point autoregressive (TVCP-AR) model. The TVCP-AR model can detect both gradual and abrupt changes in emotion dynamics. More specifically, we show that the inertia of positive affect and negative affect measured in one individual differs qualitatively in how it changes over time. Whereas the inertia of positive affect increased only gradually over time, negative affect changed both in a gradual and abrupt fashion over time. This illustrates the necessity of being able to model both gradual and abrupt changes in order to detect meaningful quantitative and qualitative differences in temporal emotion dynamics.

Keywords: dynamic modeling, change point detection, generalized additive modeling, inertia, emotion dynamics

Whereas your height will not change in a couple of days or even years, your emotions will. In fact, both due to internal (e.g., biological rhythms) and external factors (e.g., social interactions), emotional fluctuations occur within a day or even an hour (Kuppens & Verduyn, 2015). These fluctuations or emotion dynamics call for methods that can assess emotional experience across time at small enough intervals, such as ambulatory assessment, experience sampling method, and ecological momentary assessment (Houben, Van Den Noortgate, & Kuppens, 2015; Trull & Ebner-Priemer, 2013; Trull, Lane, Koval, & Ebner-Priemer, 2015). With these methods, one can measure emotional fluctuations at different time intervals, for example, every day, hour, or even every minute, leading to what is known as intensive longitudinal data (Bolger & Laurenceau, 2013; Ebner-Priemer & Trull, 2009; Walls & Schafer, 2006).

Importantly, this kind of intensive longitudinal data has shown that not only how people feel on average (i.e., mean level of one's emotion) but also the temporal dynamics of emotions is key information for a person's well-being, (Chow, Ram, Boker, Fujita, & Clore, 2005; Kuppens, Champagne, & Tuerlinckx, 2012; Verduyn, Van Mechelen, Tuerlinckx, Meers, & Van Coillie, 2009). Thus, while it is certainly essential information to know if a person has on average a high negative affect, the pattern of how negative affect changes over time is also thought to give crucial information about a person's well-being (Trull, Lane, Koval, & Ebner-Priemer, 2015).

One dynamic feature of emotions that has been of special interest in recent emotion research is *temporal dependency* or *inertia* (Kuppens et al., 2012; Suls, Green, & Hillis, 1998; Suls & Martin, 2005). Inertia can be defined as how resistant an emotion is to change. For instance, if an emotion has a high predictability over time it is likely that one stays in a certain emotion and thus that the emotion has a high spillover from one moment to the next. High inertia has therefore been defined as a decrease in the ability of a person to have emotional changes and thus as less well working (or maladaptive) emotion-regulation skills (Kuppens, Allen, & Sheeber, 2010; Kuppens & Verduyn,

Both authors contributed equally to this article.

2017). In line with this reasoning, several studies showed a positive association between high inertia and depressive symptoms or neuroticism (e.g., Brose, Schmiedek, Koval, & Kuppens, 2015; Koval, Kuppens, Allen, & Sheeber, 2012; Koval, Pe, Meers, & Kuppens, 2013; Suls et al., 1998; Wenze, Gunthert, Forand, & Laurenceau, 2009, see, however, Dejonckheere et al. 2019).

Formally, inertia can be calculated through an autocorrelation of an emotion, or by fitting, as is commonly done, an autoregressive (multilevel) model (Jahng, Wood, & Trull, 2008; Krone, Albers, Kuppens, & Timmerman, 2017; Rovine & Walls, 2006; Schuurman, Ferrer, de Boer-Sonnenschein, & Hamaker, 2016). The drawback of these models, however, is that they assume stationarity. This implies, for instance, that the average value around which an emotion is fluctuating and its temporal dependency (i.e., autocorrelation or inertia) is time-invariant (Chatfield, 2003; Hamaker, Ceulemans, Grasman, & Tuerlinckx, 2015). This stationarity assumption is problematic as studies have shown that inertia does in fact change over time. For example, Koval and Kuppens (2012) have shown that emotional inertia changes due to a social stressor. Furthermore, Bringmann et al. (2017) showed that inertia can change in an individual brought into social isolation.

Even more significantly, current theories stemming from dynamical systems theory (Scheffer et al., 2009) suggest that changes in symptoms or emotion dynamics are crucial for predicting and explaining how individuals develop psychiatric disorders (van de Leemput et al., 2014). More specifically, "critical slowing down" that is signaled by an increase in the autocorrelation of the symptoms or emotions of an individual could function as an "early warning signal" before an individual transitions from a healthy state, to, for instance, a state of depression (Nelson, McGorry, Wichers, Wigman, & Hartmann, 2017; Wichers, Groot, Psychosystems, ESM Group, & EWS Group, 2016). In this case, the person has more difficulty in recovering from perturbations and thus regulating her/his emotions (Cabrieto et al., 2019; Cramer et al., 2016). Importantly, the type of change plays a key role in these hypotheses about how individuals develop psychiatric disorders. Specifically, a gradual increase in the autocorrelation could be an important warning signal that precedes an abrupt change in which an individual transitions into a depression. Wichers et al. (2016) found initial support for such warning signals. An increase in the autocorrelation of several mood states was found before an individual transitioned into a depression after medication reduction.

This shows the need for statistical methods that can detect and model changes in the temporal emotion dynamics and thus changes in the autocorrelation over time. Although statistical developments have led to methods that can model changes in the autocorrelation, each of these methods can model only one type of change; either gradual (e.g., Bringmann, Ferrer, Hamaker, Borsboom, & Tuerlinckx, 2018; Chow et al., 2005; Chow, Zu, Shifren, & Zhang, 2011; Haslbeck & Waldorp, in press; Molenaar, De Gooijer, & Schmitz, 1992) or abrupt change (e.g., Cabrieto, Tuerlinckx, Kuppens, Grassmann, & Ceulemans, 2017; Cabrieto, Tuerlinckx, Kuppens, Hunyadi, & Ceulemans, 2018; Hamaker & Grasman, 2012). However, the models mentioned here assume gradual change and will not be able to detect or represent abrupt changes, and vice versa. This will leave researchers in the dark regarding when and how the change in autocorrelation occurred. Therefore, in order for a model to be applicable to detect changes in emotion dynamics, it is crucial that it is able to model both change processes, gradual and abrupt.

In this paper, we will introduce a new model that can detect both gradual and abrupt change in temporal emotion dynamics: the time-varying change point autoregressive (TVCP-AR) model. As a starting point this uses the time-varying autoregressive (TV-AR) model and combines it with a change point (CP) modelling approach (Bringmann et al., 2017; Hamilton, 1989).

The outline of this paper is as follows. In the next section, we will discuss these TV-AR and CP models. This is followed by an explanation of the TVCP-AR model. After this, we will showcase the TVCP-AR model with an experience sampling study of a single patient who underwent medication reduction. We end with a discussion of the possibilities and limitations of the TVCP-AR model for future research in emotion dynamics. In Electronic Supplementary Material 1, we provide technical details and show through an extensive simulation that our model performs well in circumstances common for psychological research.

The Two Models That Are the Ingredients of the TVCP-AR Model

The TV-AR Model

The TV-AR model is an extension of the AR(1) model, where the parameters can vary over time. Non-stationarity can thus be explicitly dealt with, meaning that a person's inertia is allowed to change over time. This TV-AR model is defined by:

$$y_t = \beta_{0,t} + \beta_{1,t} y_{t-1} + \varepsilon_t \quad t > 1. \tag{1}$$

In this model, both the intercept, $\beta_{0,t}$, and slope, $\beta_{1,t}$, are allowed to change gradually over time. There are various ways to impose that changes of the parameters occur gradually. This model is based on the generalized additive model (GAM) framework (Bringmann et al., 2017;

Dahlhaus, 1997; Giraitis, Kapetanios, & Yates, 2014; Wood, 2006). Here, the estimation of $\beta_{0,t}$ and $\beta_{1,t}$ is done via nonparametric smooth functions based on regression splines (Hastie & Tibshirani, 1990).

As in all models with smoothing, there is a trade-off between model fit and smoothness of the resulting estimates. In the TV-AR model, the optimal level of smoothness is derived via generalized cross-validation (Golub, Heath, & Wahba, 1979).

In practice, estimation is straightforward using the *mcgv* package in *R* (Wood, 2006).

The Change Point Model

Especially within the econometric literature, there is an abundance of models for modelling time series where the values of the parameters depend on the state, or regime, one is in. In the simplest case, one works with two regimes. Following Hamilton (1989, 1994), this model has the form:

$$y_t = \begin{cases} \beta_0 + \beta_1 y_{t-1} + \varepsilon_t & t \leq \text{CP} \\ \beta_0 + \delta + \beta_1 y_{t-1} + \varepsilon_t & t > \text{CP} \end{cases}. \qquad (2)$$

Thus, up to a certain change point (CP), the intercept of this model is β_0, and after the change point it is $\beta_0 + \delta$. Such a model with one or more abrupt changes is known as a structural change point model. In the formulation of Hamilton, the regimes before and after the change point are only different with respect to the value of the intercept, but it is straightforward to extend this to also allow for differences in the autoregressive effects. The model Hamilton specified is the basis for a broad class of models, including change point and regime switching models that are already applied in emotion research (e.g., Cabrieto et al., 2017, 2018; de Haan-Rietdijk, Gottman, Bergeman, & Hamaker, 2014; Hamaker & Grasman, 2012).

The TVCP-AR Model

The TV-AR model allows for smooth variation of the dynamics in an AR(1) process, but not for sudden changes. The structural change point model, on the other hand, does not allow for smooth changes but does allow for sudden changes. By combining these two models, we introduce the time-varying change point AR(1) model (TVCP-AR(1)), that allows for both smooth and sudden changes in the dynamics.

The sudden change can be either at an expected moment, such as the start of treatment, or a specific moment which can be pinpointed in hindsight, such as the occurrence of a life event. In those cases, the confirmatory TVCP-AR model can be used to check whether there was indeed a (significant) change at that time point and, if so, how big the change was (see Electronic Supplementary Material 1). It is, however, also possible that the sudden change takes place at some unexpected moment. In order to find such a sudden change, the exploratory TVCP-AR model can be used.

Without knowledge of where the change takes place, one should check all possible options. A change point model partitions the data into two periods: the one up to the switch and the one after the switch. For an exploratory search toward the location of the change point, we use the following algorithm.

First, fit a TV-AR model *without* change points and denote the corresponding Akaike Information Criterion (AIC) value by AIC^0. As a next step, for each $2 < i < T - 1$, perform the following actions:

(1) Fit a model with a change point at location i to the data;
(2) Denote the AIC-value of this model by AIC_i^1.

Let $\text{AIC}^1 = \text{argmin}_i \text{AIC}_i^1$ and denote the value i for which this minimum is attained by j. Compute $\text{AIC}^1 - \text{AIC}^0$. If the improvement in AIC is too small there is no indication for a change point. If, however, the AIC^1 score lies substantially below AIC^0, then location j will be denoted as the first switch point.

The simulations in Electronic Supplementary Material 1 suggest that to avoid too many false positives, a reasonable threshold for the AIC difference is somewhere between -10 and -15. However, setting the threshold is in the end a trade-off between power and false positive rate, and depends on the number of time points and the expected effect size.

Note that rather than the AIC, other information criteria, such as the Bayesian Information Criterion (BIC), can be also applied. In Electronic Supplementary Material 1, we study model selection based on both AIC and BIC and provide advice on which one to choose and which threshold to choose with it.

Note that it is undesirable to allocate change points at extreme ends of the time series. When, for instance, a change point would be allocated at $t = 2$, this implies that the first regime only has a single observation. Putting a TV-AR model on one or two observations is clearly undesirable, thus rather than applying the approach above for $2 < i < T - 1$, it makes more sense to apply it only to $k < i < T - k + 1$, for some small value of k (e.g., $k = 3$).

Once a change point has been found, the time series is partitioned into two parts. For each part, a TV-AR model is fitted, allowing also for a gradual change in the AR(1) coefficients. Furthermore, the above strategy can be applied again to find a new change point. This approach can be repeated until no further change points are detected. Figure 1 sketches the approach suggested here. A detailed explanation of this model is provided in Electronic Supplementary Material 1.

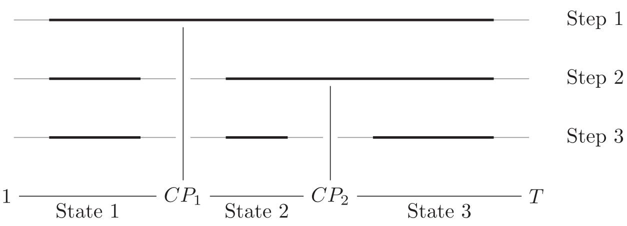

Figure 1. The exploratory procedure for finding multiple change points. Step 1 starts with the full time series 1, . . ., T and excludes a few observations at each end (depicted by a thin grey line) and searches for a change point in the remaining observations. One is found at location CP_1. In Step 2 the time series is partitioned into two: 1, . . ., CP_1 and CP_1 + 1, . . ., *T*. Both partitions have their buffer zones and in both partitions new change points are sought. No change point is found in 1, . . ., CP_1, but one is found in CP_1 + 1, . . ., *T* at location CP_2. This subdivides this second partition into two partitions and in Step 3 these are searched for a change point. In neither of them one is found, thus the model splits the time series into three states.

Empirical Example

In order to illustrate the TVCP-AR model, we analyzed data of one patient from an experience sampling study of 239 days (Wichers et al., 2016; see also Kossakowski, De Groot, Haslbeck, Borsboom, & Wichers, 2017). During this study, the patient (with major depression) underwent medication reduction, and was beeped 10 times per day to report on momentary experiences, resulting in 1,474 time points. First there was a baseline period of 28 days. After this, the trial period started (days 29–127), with medication reduction starting at day 42. This was followed by a post-trial assessment period (days 129–155), and finally an additional assessment period (days 156–239; see Figure 2). In this study, it was found based on the Symptom Checklist-90 – Revised (SCL-90-R; Derogatis, Rickels, & Rock, 1976) depression subscale that this patient had a sudden increase in depression symptoms around day 127. Here we only analyze pre-processed data for variables positive affect and negative affect (see Figures 2A and 2B). Besides Wichers et al. (2016), the same data have been previously analyzed by Cabrieto et al. (2018). Both studies indeed detected a "critical slowing down" preceding the relapse, signaled by an increase in the autocorrelation of positive and negative effect. However, these studies used analyses that could detect either gradual or abrupt changes in the autocorrrelation, but not both kinds of change simultaneously.

In order to be able to compare our study with the studies of Wichers et al. (2016) and Cabrieto et al. (2018), we used the detrended version of the data, and excluded time points for which lag 1 counterparts were not available, as well as those that were preceded by a night. The data and R-code to replicate the TVCP-AR analyses can be found in the Electronic Supplementary Material 2–6. To get an indication of the robustness of our results we used both the AIC and BIC for model selection. Following the recommendation based on our simulation study in Electronic Supplementary Material 1, we set a threshold of −15 on AIC or BIC difference for labeling the finding as evidence for a change point in the data. We used such a strict threshold in order reduce the risk of discovering false positives. All analyses of the empirical example can be found in the Electronic Supplementary Material 2–6.

Results

As the TVCP-AR is a univariate model, we analyzed positive affect and negative affect separately. Starting with positive affect, the TVCP-AR model clearly shows that there is hardly any difference in AIC from the model without to the model with change point (see Figures 2A and 2C). The largest difference in AIC is 1.68, which is clearly less than 15. Figure 2D shows the final model, which is in essence a TV-AR(1) model with a slow gradual change in autocorrelation, with no evidence of an abrupt change. Using the BIC led to the same results.

In contrast, in the negative affect data both gradual and abrupt changes can be found. Both the AIC and BIC indicated a change point at day 47 (with an AIC difference of −20.33 and a BIC difference of −20.26; see also Electronic Supplementary Material 2). A second change point was also detected, but its exact timing was less robust. Using the AIC, the change point was found around 120 days (with an AIC difference of −22.81; see Figure 2E), but also a further change point was detected around day 127, thus the same day around which the patient relapsed into depression. This change point was extremely close to the change point at day 120. Therefore, there were not enough time points between the change points at day 120 and day 127 to perform the next step of the TVCP-AR(1) model, in which the gradual change in the autocorrelation is modelled.[1] The BIC, on the other hand, indicated a BIC difference of −17.90 for a change point at day 106.

As a general pattern, the change points occurred after the medication dose reduction. There was a gradual increase of the autocorrelation before day 47, after which the autocorrelation abruptly dropped. A second increase in autocorrelation was detected before the patient relapsed into depression. The exact timing of this increase in the autoregressive parameter, however, could not be robustly determined. Based on Figure 2F, a gradual increase seemed to have started around day 80, whereas an abrupt change was detected around day 106, 120, or 127. This overall

[1] Both patterns show first an increase and then a decrease in autocorrelation.

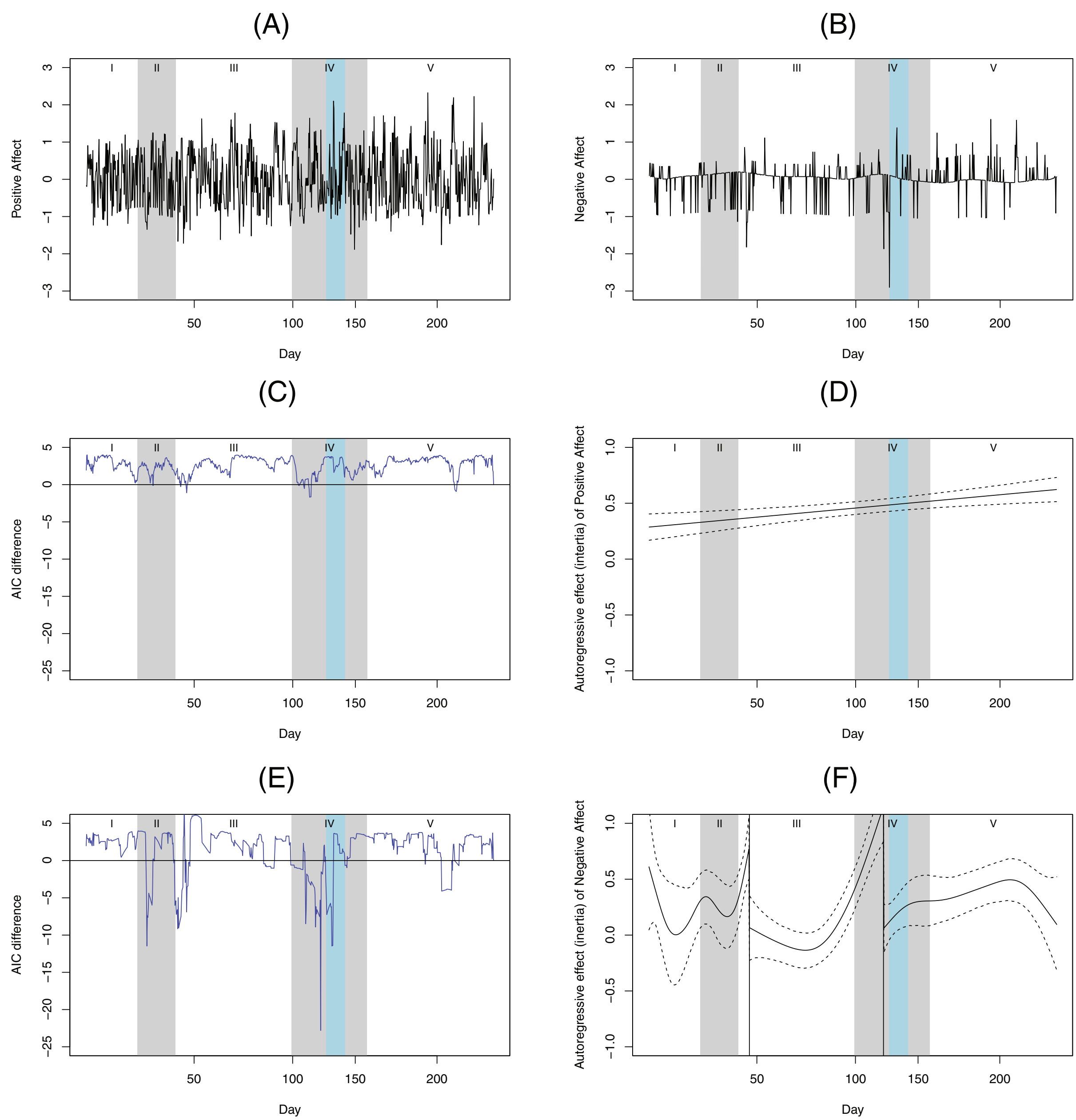

Figure 2. (A) Raw detrended Positive Affect scores; (B) raw detrended Negative Affect scores; (C) AIC difference, positive affect; (D) final model for inertia of positive affect; (E) AIC difference of negative affect for the first change point; (F) final model of inertia for negative effect. I = Baseline, II = Before Dose Reduction, III = Dose Reduction; IV = Post Assessment; V = Follow-up. The blue vertical line represents the week in which the clear increase in the severity of the symptoms occurred. Note that the days on the horizontal axis are not equally spaced. This reflects the missingness in the data: For example, between day 100 and day 150 there were more missing values than between day 50 and day 100.

period overlaps with the timing where Cabrieto et al. (2018) detected a change point (day 86).

Discussion

There is increasing evidence that emotion dynamics such as inertia change over time. Especially the literature on complex system dynamics in psychopathology calls for methods that can detect early warning signals, such as when and how changes in inertia or autocorrelation occur (Wichers, Schreuder, Goekoop, & Groen, 2019). Whereas current methods can only detect either gradual or abrupt changes in autocorrelation, we showed in this article how the TVCP-AR model can detect both gradual and abrupt changes in emotion dynamics. More specifically, we showed that in the empirical example the autocorrelations of positive and negative affect differ qualitatively in how they change over time. Whereas the autocorrelation of positive affect increases only gradually over time, negative affect changes both in a gradual and abrupt fashion. This application, thus, illustrates the necessity of modeling both gradual and abrupt changes in order to detect meaningful quantitative and qualitative differences in temporal emotion dynamics.

Importantly, the TVCP-AR is not suitable for all kinds of qualitative changes. Change point analysis as such is especially suited when abrupt changes happen several times, but unsuited when the emotion dynamics are shifting frequently between different regimes for short times. In this case, regime switching models should be used (see, e.g., Hamaker, 2009). Additionally, TVCP-AR model is a discrete time model, which limits its ability to deal with unequally spaced time points (Ryan, Kuiper, & Hamaker, 2019; Voelkle & Oud, 2013). Developing continuous forms of the TVCP-AR model would be a fruitful endeavor (e.g., along the lines of Chen, Chow, & Hunter, 2019).

Another limitation of the TVCP-AR model is that an extensive number of time points is needed in order to find gradual and abrupt changes. In general, when the effect of the abrupt change is pronounced, around 100 time points are needed (see Electronic Supplementary Material 1). However, this number increases when there is both a gradual and abrupt change or if the change in dynamics is not pronounced. A related issue is that a TVCP-AR can indicate, as in the empirical example, that two change points are fairly close to one another. In this case, the TVCP-AR could not give information on the period between these change points.

An advantage of the TVCP-AR model is that, in contrast to, for example, the method suggested by Cabrieto et al. (2018), one can distinguish between changes in the mean or the autocorrelation of the process. In the empirical example, the data were already detrended, but with the TCVP-AR model such detrending as a preprocessing step is not necessary. Instead, the TVCP-AR model can distinguish whether changes happen in the mean or the autocorrelation of the process under study (or in both). This is an important advantage, as recently there has been debate regarding the predictive value of dynamic measures such as the autoregressive coefficient over and above the mean in the context of emotion dynamic research (Dejonckheere et al., 2019).

On top of allowing for dynamic changes in mean level and inertia, our model allows for abrupt changes in the variability: for each segment (see Figure 1) a separate variance is modelled for the error terms ε_t. Changes in intraindividual variability can be indicators of psychopathological importance (Du & Wang, 2018). Within the current GAM-framework, it is unfortunately not possible to allow for gradual changes in the variation on top of the modelled abrupt changes.

The idea of early warning signals has also been incorporated into the psychological network approach (Cramer et al., 2016). In this approach, the main focus of interest is not on the inertia or autocorrelation of an emotion, but rather on the interaction between emotions or symptoms (Borsboom & Cramer, 2013). For instance, Wichers et al. (2016) showed using the same empirical dataset that not just the autocorrelations of the mental states, but also interactions between the mental states (i.e., the dynamic network) increased in strength near the transition. Current network models, however, are either based on a vector autoregressive model (Pe et al., 2015; Wigman et al., 2015), in which no change over time can be modeled, or on time-varying vector autoregressive models that can only model gradual change over time (Bringmann et al., 2018; Haslbeck, Bringmann, & Waldorp, in press; Haslbeck & Waldorp, in press). A multivariate extension of the TVCP-AR with which also the dynamics between emotions can be modeled in a gradual and abrupt is currently under development. In sum, the TVCP-AR is a powerful method for modeling and detecting different types of changes in emotion dynamics.

Electronic Supplementary Material

The electronic supplementary material is available with the online version of the article at https://doi.org/10.1027/1015-5759/a000589

1. Technical details and simulation results for the TVCP-AR model

2. The dataset used for the empirical example

3. The R code to run the analyses using AIC as the model selection criterion

4. The functions needed to run the code in #3

5. The R code to run the analyses using BIC as the model selection criterion

6. The functions needed to run the code in #5

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