Cross Recurrence Plot Based Synchronization of Time Series

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Abstract. The method of recurrence plots is extended to the cross recurrence plots (CRP), which among others enables the study of synchronization or time differences in two time series. This is emphasized in a distorted main diagonal in the cross recurrence plot, the line of synchronization (LOS). A non-parametrical fit of this LOS can be used to rescale the time axis of the two data series (whereby one of it is e.g. compressed or stretched) so that they are synchronized. An application of this method to geophysical sediment core data illustrates its suitability for real data. The rock magnetic data of two different sediment cores from the Makarov Basin can be adjusted to each other by using this method, so that they are comparable.

1 Introduction

The adjustment of data sets with various time scales occurs in many occasions, e.g. data preparation of tree rings or geophysical profiles. In geology, often a large set of geophysical data series is gained at various locations (e.g. sediment cores). That is why these data series have a different length and time scale. Before any time series analysis can be started, the data series have to be synchronized to the same time scale. Usually, this is done visually by comparing and correlating each maximum and minimum in both data sets by hand (wiggle matching), which includes the human factor of subjectiveness and is a lengthy process. An automatical and objective method for verification should be very welcome.

In the last decades some techniques for this kind of correlation and adjustment were suggested. They span graphical methods (Prell et al., 1986), inverse algorithms, e.g. using Fourier series (Martinson et al., 1982) and algorithms based on similarity of data, e.g. sequence slotting (Thompson and Clark, 1989).

However, we focus on a method based on nonlinear time series analysis. During our investigations of the method of cross recurrence plots (CRP), we have found an interesting feature of it. Besides the possibility of the application of the recurrence quantification analysis (RQA) of Webber and Zbilut on CRPs (1998), there is a more fundamental relation between the structures in the CRP and the considered systems. Finally, this feature can be used for the task of the synchronization of data sets. Although the first steps of this method are similar to the sequence slotting method, their roots are different.

First we give an introduction in CRPs. Then we explain the relationship between the structures in the CRP and the systems and illustrate this with a simple model. Finally we apply the CRP on geophysical data in order to synchronize various profiles and to show their practical availability. Since we focus on the synchronization feature of the CRP, we will not give a comparison between the different alignment methods.

2 The Recurrence Plot

Recurrence plots (RP) were firstly introduced by Eckmann et al. (1987) in order to visualize time dependent behaviour of orbits $\vec{x}_i$ in the phase space. A RP represents the recurrence of the phase space trajectory to a state. The recurrence of states is a fundamental property of deterministic dynamical systems (Argyris et al., 1994; Casdagli, 1997; Kantz and Schreiber, 1997). The main step of the visualization is the calculation of the $N \times N$-matrix

$$R_{i,j} = \Theta(\varepsilon - \|\vec{x}_i - \vec{x}_j\|), \quad i,j = 1 \ldots N,$$  \hspace{1cm} (1)

where $\varepsilon$ is a predefined cut-off distance, $\| \cdot \|$ is the norm (e.g. the Euclidean norm) and $\Theta(x)$ is the Heaviside function. The values one and zero in this matrix can be simply visualized by the colours black and white. Depending on the kind of the application, $\varepsilon$ can be a fixed value or it can be changed for each $i$ in such a way that in the ball with the radius $\varepsilon$ a predefined amount of neighbours occurs. The latter
will provide a constant density of recurrence points in each column of the RP.

The recurrence plot exhibits characteristic patterns for typical dynamical behaviour (Eckmann et al., 1987; Webber Jr. and Zbilut, 1994): A collection of single recurrence points, homogeneously and irregularly distributed over the whole plot, reveals a mainly stochastic process. Longer, parallel diagonals formed by recurrence points and with the same distance between the diagonals are caused by periodic processes. A paling of the RP away from the main diagonal to the corners reveals a drift in the amplitude of the system. Vertical and horizontal white bands in the RP result from states which occur rarely or represent extreme states. All these structures were formed by using the property of recurrence of states. It should be pointed out that the states are measured on varying time scales. These could be sets from borehole or core data in geophysics or tree rings in dendrochronology. Sediment cores might have undergone a number of coring disturbances such as compression or stretching. Moreover, cores from different sites with differing sedimentation rates would have different temporal resolutions. All these factors require a method of synchronizing.

A CRP of the two corresponding time series will not contain a main diagonal. But if the sets of data are similar e.g. only rescaled, a more or less continuous line in the CRP that is like a distorted main diagonal can occur. This line contains information on the rescaling. We give an illustrative example. A CRP of a sine function with itself (i.e. this is the CRP) contains a main diagonal (black CRP in Fig. 1). Hence, the CRPs in the Fig. 1 are computed with embeddings of dimension one, further diagonal lines from the upper left to the lower right occur. These lines typify the similarity of the phase space trajectories in positive and negative time direction.

Now we rescale the time axis of the second sine function in the following way

\[
\sin(\varphi t) \longrightarrow \sin(\varphi t + a \sin(\psi t))
\]

We will henceforth use the notion rescaling only in the mention of the rescaling of the time scale. The rescaling of the second sine function with different parameters \(\varphi\) results in a deformation of the main diagonal (green and red CRP in Fig. 1). The distorted line contains the information on the rescaling, which we will need in order to re-synchronize the two time series. Therefore, we call this distorted diagonal line of synchronization (LOS).

In the following, we present a toy function to explain the procedure. If we consider a one dimensional case without

\[
\begin{align*}
\text{Time in } f & \quad 1 \quad 2 \quad 3 \quad 4 \quad 5 \quad 6 \\
\text{Time in } g & \quad 1 \quad 2 \quad 3 \quad 4 \quad 5 \quad 6
\end{align*}
\]

Fig. 1. Cross recurrence plots of sine functions \(f(t) = \sin(\varphi t)\) and \(g(t) = \sin(\varphi t + a \sin(\psi t))\), where \(a = 0\) for the black CRP, \(a = 0.5\) for the green CRP and \(a = 1\) for the red CRP. The variation in the time domain leads to a deforming of the synchronization line.
embedding, the CRP is computed with

\[ \text{CR}(t_1, t_2) = \Theta(\varepsilon - \| f(t_1) - g(t_2) \|). \]  

(4)

If we set \( \varepsilon = 0 \) to simplify the condition, Eq. (4) delivers a recurrence point if

\[ f(t_1) = g(t_2). \]  

(5)

In general, this is an implicit condition that links the variable \( t_1 \) to \( t_2 \). Considering the physical examples of above, it can be assumed that the time series are essentially the same – that means that \( f = g \) – up to a rescaling function of time. So we can state

\[ f(t_1) = f(\phi_t(t_2)). \]  

(6)

If the functions \( f(\cdot) \) and \( g(\cdot) \) are not identical our method is in general not capable of deciding if the difference in the time series is due to different dynamics \( f(\cdot) \neq g(\cdot) \) or if it is due to simple rescaling. So the assumption that the dynamics is alike up to a rescaling in time is essential. Even though for some cases where \( f \neq g \) it can be applied in the same way. If we consider the functions \( f(\cdot) = a \cdot \tilde{f}(\cdot) + b \) and \( g(\cdot) = \tilde{g}(\cdot) \), whereby \( f(\cdot) \neq g(\cdot) \) are the observations and \( \tilde{f}(\cdot) = \tilde{g}(\cdot) \) are the states, normalization with respect to the mean and the standard deviation allows us to use our method.

\[ f(\cdot) = a \cdot \tilde{f}(\cdot) + b \rightarrow \tilde{f}(\cdot) = \frac{f(\cdot) - \langle f(\cdot) \rangle}{\sigma(f(\cdot))} \]  

(7)

\[ \tilde{g}(\cdot) = \frac{g(\cdot) - \langle g(\cdot) \rangle}{\sigma(g(\cdot))} \]  

(8)

With \( \tilde{g}(\cdot) = \tilde{f}(\cdot) \) the functions \( \tilde{f}(\cdot) \) and \( \tilde{g}(\cdot) \) are the same after the normalization. Then our method can be applied without any further modification.

In some special cases Eq. (6) can be resolved with respect to \( t_1 \). Such a case is a system of two sine functions with different frequencies

\[ f(t) = \sin(\varphi \cdot t + \alpha) \]  

(9)

\[ g(t) = \sin(\psi \cdot t + \beta) \]  

(10)

Using Eq. (5) and Eq. (6) we find

\[ \sin(\varphi \cdot t_1 + \alpha) - \sin(\psi \cdot t_2 + \beta) = 0 \]  

(11)

and one explicit solution of this equation is

\[ \Rightarrow t_2 = \phi(t_1) = \left( \frac{\varphi}{\psi} t_1 + \gamma \right) \]  

(12)

with \( \gamma = \frac{\alpha - \beta}{\psi} \). In this special case the slope of the main line in a cross recurrence plot represents the frequency ratio and the distance between the axes origin and the intersection of the line of synchronization with the ordinate reveals the phase difference. The function \( t_2 = \phi(t_1) \) (Eq. 6) is a transfer or rescaling function which allows us to rescale the second system to the first system. If the rescaling function is not linear the LOS will also be curved.

For the application one has to determine the LOS – usually non-parametrically – and then rescale one of the time series.

In the Appendix we describe a simple algorithm for estimating the LOS. Its determination will be better for higher embeddings because the vertical and cross-diagonal structures will vanish. We do not conceal that the embedding of the time series is connected with difficulties. The Takens Embedding Theorem holds for closed, deterministic systems without noise, only. If noise is present one needs its realization to find a reasonable embedding. For stochastic time series it does not make sense to consider a phase space and so embedding is in general not justified here either (Romano, to be published; Takens, 1981).

The choice of a special embedding lag could be correct for one section of the data, but incorrect for another (for an example see below). This can be the case if the data is non-stationary. Furthermore, the choice of method of computing the CRP and the threshold \( \varepsilon \) will influence the quality of the estimated LOS.

The next sections will be dedicated to application.

5 Application to a Simple Example

At first, we consider two sine functions \( f(t) = \sin(\varphi t) \) and \( g(t) = \sin(\psi t^2) \), where the time scale of the second sine differs from the first by a quadratic term and the frequency \( \psi = 0.01 \varphi \). Sediment parameters are related to such kind of functions because gravity pressure increases nonlinearly with the depth. It can be assumed that both data series come from the same process and were subjected to different depositional compressions (e.g. a squared or exponential increasing of the compression). Their CRP contains a bowed LOS (Fig. 2). We have used the embedding parameters dimension \( m = 2 \), delay \( \tau = \pi/2 \) and a varying threshold \( \varepsilon \), so that the CRP contains a constant recurrence density of 20 %. Assuming that the time scale of \( g \) is not the correct scale, we denote that scale by \( t' \). In order to determine the non-parametrical LOS, we have implemented the algorithm described in the Appendix. Although this algorithm is still not mature, we obtained reliable results (Fig. 3). The resulting rescaling function has the expected squared shape \( t = \phi(t') = 0.01 t'^2 \) (red curve in Fig. 3). Substituting the time scale \( t' \) in the second data series \( g(t') \) by this rescaling function \( t = \phi(t') \), we get a set of synchronized data \( f(t) \) and \( g(t) \) with the non-parametric rescaling function \( t = \phi(t') \) (Fig. 4). The synchronized data series are approximately the same. The cause of some differences is the meandering of the LOS, which itself is caused by partial weak embedding. Nevertheless, this can be avoided by more complex algorithm for estimating the LOS.

6 Application to Real Data

In order to continue the illustration of the working of our method we have applied it to real data from geology.

In the following we compare the method of cross recurrence plot matching with the conventional method of visual wiggle matching (interactive adjustment). Geophysical data
Fig. 2. Cross recurrence plots of two sine functions \( f(t) = \sin(\phi t) \) and \( g(t) = \sin(\psi t^2) \) which is the base for the determination of the rescaling function between both data series. The embedding parameters were dimension \( m = 2 \), delay \( \tau = \pi/2 \) and a varying threshold \( \varepsilon \), in such a way that the CRP contains a constant recurrence density of 20%.

Fig. 3. The rescaling function (black) determined from the CRP in Fig. 2. It has the expected parabolic shape of the squared coherence in the time domain. In red the square function.

Fig. 4. Reference data series (upper panel) and rescaled data series before (red) and after (black) rescaling by using the rescaling function of Fig. 3 (lower panel).

Fig. 5. ARM data of the boreholes PS 2178-3 GPC and PS 2180-2 GPC in the Central Arctic Ocean before adjustment.

of two sediment cores from the Makarov Basin, central Arctic Ocean, PS 2178-3 and PS 2180-2, were analysed. The task should be to adjust the data of the PS 2178-3 data (data length \( N = 436 \)) to the scale of the PS 2180-2 (data length \( N = 251 \)) in order to get a depth-depth-function which allows to synchronize both data sets (Fig. 5).

We have constructed the phase space with the normalized six parameters low field magnetic susceptibility \( (\kappa_{LF}) \), anhysteretic remanent magnetization \( (ARM) \), ratio of anhysteretic susceptibility to \( (\kappa_{AR}/\kappa_{LF}) \), relative palaeointensity \( (PJA) \), median destructive field of \( ARM (MDF_{ARM}) \) and inclination \( (INC) \). A comprehensive discussion of the data is given in Nowaczyk et al. (2001). The embedding was combined with the time-delayed method according to (Takens, 1981) in order to increase further the dimension of the phase-space with the following rule: If we have \( n \) parameters \( a_i \), the embedding with dimension \( m \) and delay \( \tau \) will result in a \( (m \cdot n) \)-dimensional phase space:

\[
\vec{x}(t) = (a_1(t), \ldots, a_n(t), a_1(t+\tau), \ldots, a_n(t+\tau), a_1(t+2\tau), \ldots, a_n(t+2\tau), \ldots, a_1(t+(m-1)\tau), \ldots, a_n(t+(m-1)\tau))
\]  

(13)

For our investigation we have used a dimension \( m = 3 \) and a delay \( \tau = 1 \), which finally led to a phase space of
dimension 18 ($3 \times 6$). The recurrence criterion was $\varepsilon = 5\%$ nearest neighbours.

The resulting CRP shows a clear LOS and some clustering of black patches (Fig. 6). The latter occurs due to the plateaus in the data. The next step is to fit a non-parametric function (the depth-depth-curve) to the LOS in the CRP (red curve in Fig. 6). With this function we are able to adjust the data of the PS 2178-3 core to the scale of PS 2180-2 (Fig. 8).

The determination of the depth-depth-function with the conventional method of visual wiggle matching is based on the interactive and parallel searching for the same structures in the different parameters of both data sets. If the adjustment does not work in a section of the one parameter, one can use another parameter for this section, which allows the multivariate adjustment of the data sets. The recognition of the same structures in the data sets requires a degree of experience. However, human eyes are usually better in the visual assessment of complex structures than a computational algorithm.

Our depth-depth-curve differs slightly from the curve which was gained by the visual wiggle matching (Fig. 7). However, despite our (still) weak algorithm to fit the non-parametric adjustment function to the LOS, we obtained a good result of adjusted data series. If they are well adjusted, the correlation coefficient between the parameters of the adjusted data and the reference data should not vary so much. The correlation coefficients between the reference and adjusted data series is about $0.70 - 0.80$, where the correlation coefficients of the interactive rescaled data varies from $0.71 - 0.87$ (Tab. 1). The $\chi^2$ measure of the correlation coefficients emphasizes more variation for the wiggle matching than for the CRP rescaling.

7 Discussion

Cross recurrence plots (CRP) reveal similarities in the states of the two systems. A similar trajectory evolution gives a diagonal structure in the CRP. An additional time dilatation or compression of one of these similar trajectories causes a distortion of this diagonal structure (Fig. 1). This effect is used to look into the synchronization between both systems. Synchronized systems have diagonal structures along and in the direction of the main diagonal in the CRP. Interruptions of these structures with gaps are possible because of variations in the amplitudes of both systems. However, a loss of synchronization is viewable by the distortion of this structures along the main diagonal (LOS). By fitting a non-parametric function to the LOS one allows to re-synchronization or adjustment to both systems at the same time scale. Although this method is based on principles from deterministic dynamics, no assumptions about the underlying systems has to be made.

Table 1. Correlation coefficients $\varrho_{1, 2}$ between adjusted data and reference data and their $\chi^2$ deviation. The correlation of the interactive adjusted data varies more than the automatic adjusted data. The data length is $N = 170$ (wiggle matching) and $N = 250$ (CRP matching). The difference between the both correlation coefficients $\varrho_1$ and $\varrho_2$ is significant at a 99% significance level, when the test measure $\hat{z}$ is greater than $z_{0.01} = 2.576$.

| Parameter | $\varrho_1$, wiggle matching | $\varrho_2$, CRP matching | $\hat{z}$ |
|-----------|-------------------------------|--------------------------|---------|
| ARM       | 0.8667                        | 0.7846                   | 6.032   |
| MDF$_{ARM}$ | 0.8566                      | 0.7902                   | 4.791   |
| $\kappa_{LF}$ | 0.7335                     | 0.7826                   | 2.661   |
| $\kappa_{ARM}/\kappa_{LF}$ | 0.8141                    | 0.8049                   | 0.614   |
| PJA       | 0.7142                        | 0.6995                   | 0.675   |
| INC       | 0.7627                        | 0.7966                   | 1.990   |
| $\chi^2$  | 141.4                         | 49.1                     |        |
made in order for the method to work.

The first example shows the obvious relationship between the LOS and the time domains of the considered time series. The squared increasing of the frequency of the second harmonic function causes a parabolic LOS shape in the CRP (Fig. 2). Finally, with this LOS we are able to rescale the second function to the scale of the first harmonic function (Fig. 4). Some differences in the amplitude of the result are caused by the algorithm used in order to extract the LOS from the CRP. However, our concern is to focus on the distorted main diagonal and their relationship with the time domains.

The second example deals with real geological data and allows a comparison with the result of the conventional method of visual wiggle matching. The visual comparison of the adjusted data shows a good concordance with the reference and the wiggle matched data (Fig. 8 and 9). The depth-depth-function differs up to 20 centimeters from the depth-depth-function of the wiggle matching. The correlation coefficients between the CRP adjusted data and the reference data varies less than the correlation coefficients of the wiggle matching. However, the correlation coefficients for the CRP adjusted data are smaller than these for the wiggle matched data. Although their correlation is better, it seems that the interactive method does not produce a balanced adjusting, whereas the automatic matching looks for a better balanced adjusting.

These both examples exhibits the ability to work with smooth and non-smooth data, whereby the result will be better for smooth data. Small fluctuations in the non-smooth data can be handled by the LOS searching algorithm. Therefore, smoothing strategies, like smoothing or parametrical fit of the LOS, are not necessary. The latter would damp one advantage of this method, that the LOS is yielded as a non-parametrical function. A future task will be the optimization of the LOS searching algorithm, in order to get a clear LOS even if the data are non-smooth. Further, the influence of dynamical noise to the result will be studied. Probably, this problem may be bypassed by a suitable LOS searching algorithm too.

Our method has conspicuous similarities with the method of sequence slotting described by Thompson and Clark (1989). The first step in this method is the calculation of a distance matrix similar to our Eq. 2, which allows the use of multivariate data sets. Thompson and Clark (1989) referred to the distance measure as dissimilarity. It is used to determine the alignment function in such a way that the sum of the dissimilarities along a path in the distance matrix is minimized. This approach is based on dynamic programming methods which were mainly developed for speech pattern recognition in the 70’s (e.g. Sakoe and Chiba, 1978). In contrast, RPs were developed to visualize the phase space behaviour of dynamical systems. Therefore, a threshold was introduced to make recurrent states visible. The involving of a fixed amount of nearest neighbours in the phase space and the possibility to increase the embedding dimensions distinguish this approach from the sequence slotting method.
8 Conclusion

The cross recurrence plot (CRP) can contain information about the synchronization of data series. This is revealed by the distorted main diagonal, which is called line of synchronization (LOS). After isolating this LOS from the CRP, one obtains a non-parametric rescaling function. With this function, one can synchronize the time series. The underlying more-dimensional phase space allows to include more than one parameter in this synchronization method, as it usually appears in geological applications, e.g., core synchronization. The comparison of CRP adjusted geophysical core data with the conventionally visual matching shows an acceptable reliability level of the new method, which can be further improved by a better method for estimating the LOS. The advantage is the automatic, objective and multivariate adjustment. Finally, this method of CRPs can open a wide range of applications as scale adjustment, phase synchronization and pattern recognition for instance in geology, molecular biology and ecology.

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Appendix: An Algorithm to Fit the LOS

In order to implement a recognition of the LOS we have used the following simple two-step algorithm. Denote all recurrence points by \( r_{i,\alpha,j,\beta} \) (\( \alpha = 1, 2, \ldots \)) and the recurrence points lying on the LOS by \( r_{\alpha,\beta} \). Before the common algorithm starts, find the recurrence point \( r_{1,1} \) next to the axes origin. In the first step, the next recurrence point \( r_{1,1+1,\alpha,\beta} \) after a previously determined recurrence point \( r_{1,1,\alpha,\beta} \) is to be determined. This is carried out by a stepwise increasing of a squared \((w \times w)\) sub-matrix, wherein the previous recurrence point is at the \((1,1)\)-location. The size \( w \) of this sub-matrix increases stepwise until it meets a new recurrence point or the margin of the CRP. When a next recurrence point \( r_{\alpha+1,1,\beta,\beta} \) (\( \delta_i = w \) or \( \delta_j = w \)) in the \( x \)-direction (\( y \)-direction) is found, the second step looks if there are following recurrence points in \( y \)-direction (\( x \)-direction). If this is true (e.g., there are a cluster of recurrence points) increase further the sub-matrix in \( y \)-direction (\( x \)-direction) until a predefined size \((w + d\delta_x) \times (w + d\delta_y)\) \((d\delta_x < dx, d\delta_y < dy)\) or until no new recurrence points are met. This further increasing of the sub-matrix is done for the both \( x \)- and \( y \)-direction. Using \( d\delta_x, d\delta_y \) we compute the next recurrence point \( r_{\alpha+1,1,\beta+1} \) by determination of the center of mass of the cluster of recurrence points with \( i_{\alpha+1} = i_\alpha + (d\delta_x + \delta_i)/2 \) and \( j_{\beta+1} = j_\beta + (d\delta_y + \delta_j)/2 \). The latter avoids the fact that the algorithm is driven around widespread areas of recurrence points. Instead of this, the algorithm locates the LOS within these areas. (However, the introducing of two additional parameter \( dx \) and \( dy \) is a disadvantage which should be avoided in further improvements of this algorithm.) The next step is to set the recurrence point \( r_{\alpha+1,1,\beta+1} \) to a new start point and to begin with the step one in order to find the next recurrence point. These steps are repeated until the end of the RP is reached.

We know that this algorithm is merely one of many possibilities. The following criteria should be met in order to obtain a good LOS. The amount of targeted recurrence points by the LOS \( N_1 \) should converge to the maximum and the amount of gaps in the LOS \( N_0 \) should converge to the minimum. An analysis with various estimated LOS confirms this requirement. The correlation between two LOS-synchronized data series arises with \( N_1 \) and with \( 1/N_0 \) (the correlation coefficient correlates most strongly with the ratio \( N_1/N_0 \)).

The algorithm for computation of the CRP and recognition of the LOS are available as Matlab programmes on the WWW: http://www.agndl.uni-potsdam.de/~marwan.

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