Identification of synchronization intervals given two time series – Instructions for MATLAB© scripts

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1 Background

Modern computer vision approaches allow the assessment of individual motion behavior based on video recordings. Starting from the point that motion behavior of two persons is assessed with Motion Energy Analysis (MEA), the attached MATLAB© scripts identify intervals of movement synchronization respectively time series intervals in which one person predict the time series values of the other. A detailed explanation can be found in [1] (in German) and [2]. The work principal is described by [3]. Further applications are presented in [4] and [5]. A simulation study of [2] examined whether the quality of identification of synchronization intervals depends on transformation of time series (e.g. box-cox-transformation), degree of time series smoothing, size of window, and R-square-cut-off-value. The parameters which were identified as optimal are reported below. The concordance of multiple synchronization measures (respectively algorithms and their outputs) examined by [6]. Against the assumption, they found that synchronization measures (in total N=14) only partially correlated with each another. An exploratory factor analysis suggested that three different main facets of synchronization. One facet is "the strength of matching and echoing within the total interaction", another facet is "strength and *frequency* of local matching and echoing within the identified synchronization intervals". The attached algorithms (respectively their output) are categorized by [6] to the latter facet.

The attached MATLAB© scripts regarding time series analysis with window cross-lagged correlation (WCLC), window cross-lagged regression (WCLR) and peak-picking algorithm were written and developed by Uwe Altmann. Please cite [1]. In an ongoing project of the Institute of Psychosocial Medicine and Psychotherapy (Jena, Germany), the scripts were extended by Désirée Thielemann so that pre-processing steps (e.g. smoothing) and sub-routines of time series analysis run with one script. You can apply the attached scripts on your own data.

Please note, that it is assumed that two motion energy time series are given, and that the corresponding video has 25 frames per second. Filtering irregular jumps caused by video errors and standardized of time series (for more details see [1]) is recommend before the application of the attached scripts.

2 Dataset: MEA_example.txt

This is a dataset example. Each line represents a time point respectively a video frame. Each column contains standardized motion energy values. Due to the standardization, zero means that the person has not moved (no pixel with color intensity changes detected) whereas 100 indicates maximal movement (all pixel of ROI were activated).

- Column 1: motion energy of person A referring to the body
- Column 2: motion energy of person B referring to the body
- Column 3: motion energy of background ROI left (for detection of irregular jumps caused by video errors)

- Column 4: motion energy of background ROI right (for detection of irregular jumps caused by video)
- Column 5: motion energy of person A referring to the head
- Column 6: motion energy of person B referring to the head errors

Please note that the attached algorithms examine a pair of time series, for example body motions of A and B (column 1 and 2) or for example head motions of A and B (column 5 and 6).

3 Function: analyse_time_series.m

All steps of time series are done with this script. Given the file name of dataset (e.g. `c:\temp\MEA_example.txt`), it starts step by step the right sub-routine, namely `transformation_v02.m`, `smoothing.m`, `compute_WCLC.m` (or `compute_WCLR.m`), and `find_all_sync_intervals_v06.m`. The latter starts the sub-routines `clear_overlapping_sync_intervals.m` and `sync_intervals_frame2time.m`.

3.1 Input parameters for analyse_time_series

- `TSname`: Please specify time series with complete path
- `method`: Please choose 'WCLC' for windowed cross-lagged correlation with peak picking algorithm or 'WCLR' for windowed cross-lagged regression with peak picking algorithm
- `trans`: Please choose transformation, possible options: 'rawdata' = no transformation, 'log_trans' = logarithm transformed time series, 'anscombe_trans' = anscombe transformation
- `smooth`: Please choose smoothing degree, possible options: 'rawdata' = no smoothing, 'slight_smooth' = slight smoothing with smoothing splines, 'high_smooth' = high smoothing with smoothing splines

Which parameter configuration provides the best identification quality, was examined in the simulation study of [2]. For simulated time series pairs in which synchronization intervals were defined by data generation, they found that `method` ='WCLR', `trans` ='rawdata, `smooth` ='slight_smooth' showed the best identification quality. However, if time series of a real world dataset were used in which synchronization intervals defined by a human observer, then parameter configuration `method` ='WCLC', `trans` ='log_trans', `smooth` ='rawdata' provides the best identification quality.

3.2 Adjustments within the function analyse_time_series.m

- Set fixed parameters within the function (Step 1)
  - Specify bandwidth, maximum time lag and step
  - If not specified, bandwidth = 125, maximum time lag =125, step = 1 are used

- Set length of the time series (Step 2)
  - Specify the length of the time series
  - If not specified, length will be set to 1000

- after adjusting values (Step 1, 2) run WCLC/WCLR with command (adjust path)

```
analyse_time_series('G:\IMPsych-TIMPATHIN\02_Matlab\2017-11-14_Script_Sharing_WCLR\MEA_example.txt', 'WCLC', 'log_trans', 'rawdata')
```

3.3 Output

The output of `analyse_time_series.m` (resp. sub-routine `find_all_sync_intervals_v06.m`) is a list of synchronization intervals (so called: `losi`). This list contains every identified synchronization interval with its time lag (column 1), start frame (column 2), end frame (column 3) and average R^2 (column 4).

Based on that list, the frequency of synchronization can be computed (ratio of sum of all synchronization interval length and total duration of the sequence) [1] [3]. The synchronization frequency of the example (Dataset: MEA_example.txt) is 0.5810, if the parameter settings WCLC, log_trans, rawdata are used. A value of 0.5810 means that 58% of interaction time, the movement curves were synchronous.

Please be careful with interpretation. First, it should be kept in mind what the values of analyzed time series represent. In the case of motion energy time series, all body motions (e.g. head, hand, and torso) are aggregated to one intensity measure. The information which body part moved and the direction of movement is lost when motion energy is computed. On that reason algorithms for synchronization identification cannot take such information into the account, because body part and direction of movement are not measured with MEA. Furthermore, the algorithms assume that both interaction partners see each other for the entire interaction. Violations of these assumptions (which occur in natural interpersonal interactions) can result in wrong synchronization detection. However, the algorithms and their detection quality were proofed by [2]. In the case of simulated time series (in which the true beginning and ending of synchronization intervals are known), the algorithms showed a very good detection rate (given the recommended parameter settings). But if the algorithms should identify synchronization intervals which are based on video clips and are subsequently defined by human ratings, the identification quality decrease [2].

4 Literatur

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