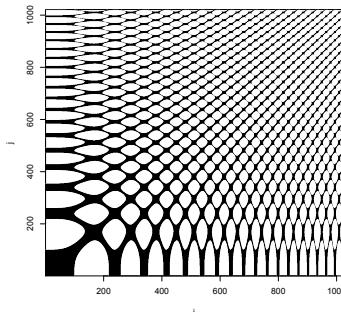


STATISTICAL DATA ANALYSIS: RECURRENCE PLOT

GÜNTHER SAWITZKI



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gs@statlab.uni-heidelberg.de .

1. BACKGROUND

1.1. Takens' Recurrence States. Recurrence plots have been introduced in an attempt to understand near periodic behaviour in hydrodynamics, in particular the transition to turbulence. On the one hand, and extended theory on dynamical systems was available, covering deterministic models. A fundamental concept is that at a certain time a system is in some state, and developing from this. Defining the proper state space is a critical step in modelling.

The other toolkit is that of stochastics processes, in particular Markov models. Classical time series assumes stationarity, and this is obviously not the way to go. A fundamental idea for Markov models is that the system state is seen in a temporal context: you have a Markov process, if you can define a (non-anticipating) state that has sufficient information for prediction: given this state, the future is independent from the past.

Recurrence, coming back to some state, is often a key to understand a near periodic system. A classical field is the movement of celestial bodies.

Hydrodynamics is a challenging problem. Understanding planetary motion is a historical challenge, and may be useful as an illustration.

As a simple illustration, let $x = (x_i)$ be a sequence, maybe near periodic. For now, think of i as a time index.

Recurrence plots have two steps. The first was a bold step by Floris Takens. If you do not know the state space of a system, for a choice of “dimension” d , take the sequence of d tuples taken from your data to define the states.

$$u_i = (x_i, \dots, x_{i+(d-1)})$$

This is Takens' delay embedding state (re)construction [1981].

As a mere technical refinement: you may know that your data are a flattened representation of m dimensional data. So you take

$$u_i = (x_i, x_{i+m}, \dots, x_{i+(d-1)*m}).$$

This may be a relict of FORTRAN times, where it was common to flatten two-dimensional structures by case.

Conceptually, you define states by observed histories. For classical Markov setup, the state is defined by the previous information x_{i-1} , but for more complex situations you may have to step back in the past. Finding the appropriate d is the challenge. So it may be appropriate to view the Takens' states as a family, indexed by the time scope d . The rest is structural information how to arrange items.

Of course it is possible to compress information here, sorting states and removing duplicates. Keeping the original definition as the advantage that we have the index i , so that u_i is the state at index position i .

But the states may have an inherent structure, which we may take into account or ignore. Since for this example, we are just in 4-dimensional space, marginal scatterplots may give enough information.

Takens' states are vectors in M dimensions. There are standard statistical techniques to visualise aspects of M dimensional vectors, at least for not too high dimension. One is the draftsman's plot, a scatterplot matrix by marginals. For Takens states, this is

ToDo: add support
for higher dimensional signals

implemented as `statepairs()`. The other is coplots, a variant of scatterplot matrix by marginals, conditioned by one or two additional variables. For Takens states, this is implemented as `statecoplots()`

To display the Takens state space, we us a variant of pairs().

By convention, the states are defined using overlapping sliding windows. This imposes considerable dependence between the states: one state is the shifted previous states, with only the end sub-state replaced. As an option, the states can be subsampled, using only non-overlapping ranges.

The Takens states may be stationary, that is asymptotically the states starting at i do not depend on i . In this case, the first row (or column) contains all information, and pairs plot form an inclusion sequence by. In general, we will use state plots in 4 or 8 dimensions, where the limits are suggested by the print area.

The visual impression of recurrence plots are strongly affected by the coverage, controlled by the radius used to determine neighbourhoods. So far, this parameter is chosen visually, and comparison needs some care.

ToDo: the Takens' state plot may be critically affected by outliers. Find a good rescaling.

ToDo: consider dimension-adjusted radius

1.2. Recurrence Plots. The next step, taken in Eckmann *et al.* [1987] was to use a two dimensional display. Take a scatterplot with the Taken's states a marginal. Take a sliding window of your process data, and for each i , find the “distance” of u_i from and to any of the collected states. If the distance is below some chosen threshold, mark the point (i, j) for which $u(j)$ is in the ball of radius $r(i)$ centred at $u(i)$.

The original publication Eckmann *et al.* [1987] actually used a nearest neighbourhood environment to cover about 10 data points.

The construction has considerable arbitrary choices. The critical radius may depend on the point i . In practical applications, using a constant radius is a common first step. Using a dichotomous marking was what presumably was necessary when the idea was introduced. With todays technology, we can allow a markup on a finer scale, as has been seen in Orion-1.

ToDo: support distance instead of 0/1 indicators

We can gain additional freedom by using a correlation view: instead of looking from one axis, we can walk along the diagonal, using two reference axis.

Helpful hints how to interpret recurrence plots are in “Recurrence Plots At A Glance” <<http://www.recurrence-plot.tk/glance.php>>, for example Figure 1

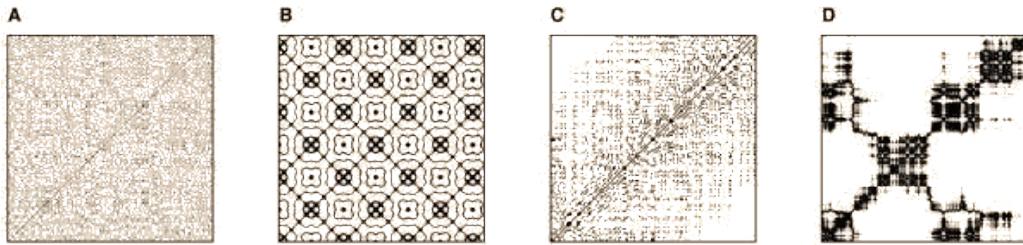


FIGURE 1. Characteristic typology of recurrence plots: (A) homogeneous (uniformly distributed noise), (B) periodic (super-positioned harmonic oscillations), (C) drift (logistic map corrupted with a linearly increasing term) and (D) disrupted (Brownian motion). These examples illustrate how different RPs can be. The used data have the length 400 (A, B, D) and 150 (C), respectively; no embeddings are used; the thresholds are $\epsilon = 0.2$ (A, C, D) and $\epsilon = 0.4$ (B). From <<http://www.recurrence-plot.tk/glance.php>>

1.3. Recurrence Quantification Analysis. While visual inspection is the prime way to assess recurrence plots, quantification of some aspects revealed of the plot may be helpful. A collection of indices is provided by a recurrence quantification analysis (RQA) Zbilut and Webber [2006], Webber Jr and Zbilut [2005].

See Table 1 on the next page.

2. R SETUP

Input

```
save.RNGseed <- 87149 #.Random.seed
save.RNGkind <- RNGkind()
```

TABLE 1. Recurrence Quantification Analysis (RQA)

<i>REC</i>	Recurrence. Percentage of recurrence points in a recurrence Plot.
<i>DET</i>	Determinism. Percentage of recurrence points that form diagonal lines.
<i>LAM</i>	Percentage of recurrent points that form vertical lines.
<i>RATIO</i>	Ratio between <i>DET</i> and <i>RR</i> .
<i>Lmax</i>	Length of the longest diagonal line.
<i>Lmean</i>	Mean length of the diagonal lines.
<i>DIV</i>	The main diagonal is not taken into account.
<i>Vmax</i>	Inverse of <i>Lmax</i> .
<i>Vmean</i>	Longest vertical line.
	Average length of the vertical lines.
<i>ENTR</i>	This parameter is also referred to as the Trapping time.
<i>TREND</i>	Shannon entropy of the diagonal line lengths distribution
<i>diagonalHistogram</i>	Trend of the number of recurrent points depending on the distance to the main diagonal
<i>recurrenceRate</i>	Histogram of the length of the diagonals. Number of recurrent points depending on the distance to the main diagonal.

```
set.seed(save.RNGseed, save.RNGkind[1])
save.RNGkind
```

Output

```
[1] "Mersenne-Twister" "Inversion"
```

Input

```
options(warn=1)
```

Input

```
laptimes <- function(){
  return(round(structure(proc.time() - chunk.time.start, class = "proc_time")[3],3))
  chunk.time.start <- proc.time()
}
```

Input

```
if (!require("sintro")) {
  # install.packages("sintro", repos="http://r-forge.r-project.org", type="source")
  library(sintro)
}
if (!require("nonlinearTseries")) {
  install.packages("nonlinearTseries")
  library(nonlinearTseries)
}
```

2.0.1. *Takens States.* Takens states are represented as a matrix, one state per row. The number of columns is the imbedding dimension. If present, the `time.lag` attribute is the lag parameter, `id` an identification string for the basic data set.

ToDo: improve choice of alpha

<i>Input</i>	
<code>alpha=0.5</code>	
<code>statepairs</code>	<i>Show marginal scatterplots of Takens states</i>

Usage.

```
statepairs(states, main,
range = NULL,
rank = FALSE, nooverlap = FALSE,
col,...)
```

Arguments.

<code>states</code>	A matrix: Takens states by dimension, one state per row.
<code>main</code>	Optional: the main header.
<code>range</code>	Optional: an interval selecting values to be displayed.
<code>rank</code>	An experimental variant. If <code>rank</code> , the values are rank transformed.
<code>nooverlap</code>	An experimental variant. If <code>nooverlap</code> , the cases are subsampled by dimension.
<code>col</code>	The current choice is $rgb(0,0,0, \alpha = \sqrt{\frac{1}{nr\ states}})$ as a default.

ToDo: colour by time

<i>Input</i>	
<code>statepairs <- function(states, main,</code>	
<code>rank=FALSE, nooverlap= FALSE, range=NULL,</code>	
<code>col = rgb(1,0,0, 1/sqrt(dim(states)[1])), ...){</code>	
<code>n <- dim(states)[1]; dim <- dim(states)[2]</code>	
<code>time.lag <- attr(states,"time.lag");</code>	
<code>if (is.null(time.lag)) time.lag <- 1</code>	
<code>if (missing(main)) {</code>	
<code>stateid <- attr(states, "id")</code>	
<code>if (is.null(stateid)) stateid <- deparse(substitute(states))</code>	
<code>main <- paste("Takens states:", stateid, "\n",</code>	
<code>"n:", n, " dim:", dim)</code>	
<code>if (time.lag != 1) main <- paste(main, " time lag:", time.lag)</code>	
<code>}</code>	
<code>if (nooverlap) {states <- states[seq(1,n, by=dim),]</code>	
<code>main <- paste(main, " no overlap")}</code>	
<code>if (!is.null(range)) { states[states[] < range[1]] <- NA;</code>	
<code>states[states[] > range[2]] <- NA</code>	
<code>main <- paste(main, " trimmed")}</code>	
<code>if (rank) {states <- apply(states, 2, rank, ties.method="random")</code>	
<code>main <- paste(main, " ranked")}</code>	
<code>#</code>	
<code>pairs(states, main=main,</code>	
<code>col=rgb(0,0,0, alpha), pch=19, ...)</code>	

```

    col=      col, pch=19, ...)
#title(main=main, outer=TRUE, line=-2, cex.main=0.8)
}

```

Assuming the index is time, the `statecoplot()` is layed out to show the highest index as response, i.e. $(x_{t-1}, x_t | x_{t-2}, x_{t-3})$.

ToDo: extend for low dimensions, extend parameters

statecoplot*Show conditioning marginal scatterplots of Takens states*

Usage.

```

statecoplot(states, main,
range = NULL,
rank = FALSE, nooverlap = FALSE,
col= rgb(0, 0, 0, \alpha = \sqrt{\frac{1}{nr\ states}}),
number = c(5,5))

```

Arguments.

<code>states</code>	A matrix: Takens states by dimension, one state per row.
<code>main</code>	Optional: the main header.
<code>range</code>	Optional: an interval selecting values to be displayd.
<code>rank</code>	An experimental variant. If <code>rank</code> , the values are rank transformed.
<code>nooverlap</code>	An experimental variant. If <code>nooverlap</code> , the cases are subsampled by dimension.
<code>alpha</code>	
<code>col</code>	The current choice is $rgb(0, 0, 0, \alpha = \sqrt{\frac{1}{nr\ states}})$, as a default.
<code>number</code>	integer; the number of conditioning intervals, for a and b, possibly of length 2.

Input

```

statecoplot <- function(states, main,
                         rank = FALSE, nooverlap = FALSE, range = NULL,
                         col = rgb(1,0,0, 1/sqrt(dim(states)[1])),
                         number = c(5,5), ...){
  n <- dim(states)[1]; dim <- dim(states)[2]
  time.lag <- attr(states,"time.lag")
  if (is.null(time.lag)) time.lag <- 1
  if (missing(main)) {
    stateid <- attr(states, "id")
    if (is.null(stateid)) stateid <- deparse(substitute(states))
    main <- paste("Takens states:", stateid, "\n",
                 "n=", n, " dim=", dim)
    if (time.lag != 1) main <- paste(main, " time lag=", time.lag)
  }

  if (nooverlap) {states <- states[ seq(1,n, by=dim),]
  main <- paste(main, " no overlap")}

  if (!is.null(range)) {
    states[states[] < range[1]] <- NA;
    states[states[] > range[2]] <- NA
    main <- paste(main, " trimmed")}
}

```

```

if (rank) {states <- apply(states, 2, rank, ties.method="random")
main <- paste(main, " ranked")}

coplot((states[,4]^states[,3]/states[,1]+ states[,2]),
number=number, main=main,
col=rgb(0,0,0, alpha), pch=19, ...)
#title(main=main, outer=TRUE, line=-2, cex.main=0.8)
}

```

2.0.2. *Local Bottleneck: Recurrence Plots.* To allow experimental implementations, functions from `nonlinearTseries` are aliased here.

Input

```

local.buildTakens <- function (time.series,
                                embedding.dim, time.lag=1,
                                id=deparse(substitute(time.series)))
{
  takens <-
    nonlinearTseries:::buildTakens(time.series, embedding.dim, time.lag)
  attr(takens, "time.lag") <- time.lag
  attr(takens, "embedding.dim") <- embedding.dim
  attr(takens, "id") <- id
  return(takens)
}

```

Input

```

local.findAllNeighbours <- function (takens, radius, number.boxes = NULL)
{
  allneighs <-
    nonlinearTseries:::findAllNeighbours(takens, radius, number.boxes = NULL)
  mostattributes(allneighs) <- attributes(takens)
  attr(allneighs, "radius") <- radius
  return(allneighs)
}

```

Input

```

#non-sparse variant
#local.recurrencePlotAux <- nonlinearTseries:::recurrencePlotAux
local.recurrencePlotAux = function(neighs, dim=NULL, lag=NULL, radius=NULL){

  # just for reference. This function is inlined
  neighbourListNeighbourMatrix = function(){
    neighs.matrix = Diagonal(ntakens)
    for (i in 1:ntakens){
      if (length(neighs[[i]])>0){
        for (j in neighs[[i]]){
          neighs.matrix[i,j] = 1
        }
      }
    }
    return (neighs.matrix)
  }

  ntakens=length(neighs)
  neighs.matrix <- matrix(nrow=ntakens, ncol=ntakens)
  #neighbourListNeighbourMatrix()
}

```

minor cosmetics
added to recurrence-
PlotAux

To Do: propagate
parameters from
`buildTakens` and
`findAllNeighbours`
in a slot of the result,
instead of using ex-
plicit parameters in
`recurrencePlotAux`.

```

#neighs.matrix = Diagonal(ntakens)
for (i in 1:ntakens){
    neighs.matrix[i,i] = 1 # do we want the diagonal fixed to 1
    if (length(neighs[[i]])>0){
        for (j in neighs[[i]]){
            neighs.matrix[i,j] = 1
        }
    }
}

#! clean up. only one main id should be presentes
main <- paste("Recurrence Plot: ",
              deparse(substitute(neighs))
              )
id <- attr(neighs, "id"); if (!is.null(id)) main <- paste(main, " id:",id)

more <- NULL

more <- paste(more," n:",length(neighs))

#use components of neights if available
embedding.dim <- attr(neighs, "embedding.dim")
if (is.null(embedding.dim)) embedding.dim <- dim
if (!is.null(dim)) {
    if (embedding.dim != dim)
        warning(paste("Embedding dim:", embedding.dim,
                      " does not match dim argument=", dim))
    more <- paste(more," dim:",dim)
}

attrradius <- attr(neighs, "radius")
if (!is.null(lag)) more <- paste(more," lag:",lag)
if (is.null(radius)) radius <- attrradius
if (!is.null(radius)) {
    more <- paste(more," radius:",radius)
    if (!is.null(attrradius) && (attrradius != radius))
        warning(paste("Radius attribute:", attrradius,
                      " does not match radius argument=", radius))
}
# if (!is.null(attrradius)) more <- paste(more," radius attr:",attrradius)
if (!is.null(more)) main <- paste(main,"\n",more)

# need no print because it is not a trellis object!!
#print(
#    image(x=1:ntakens, y=1:ntakens,
#          z=neighs.matrix,xlab="i", ylab="j",
#          col="black",
#          xlim=c(1,ntakens), ylim=c(1,ntakens),
#          useRaster=TRUE, #? is this safe??
#          main=main
#    )
#)
}

```

2.0.3. *Recurrence Plots: RQA Information.* This is a hack to report RQA information. *dim = NULL* is added to align calling with other functions.

ToDo: improve feedback for data structures in *non-linearTseries*

ToDo: improve to a full `show` method for class `rqa`.

Needs improvement.

```

Input
showrqa <- function(takens, dim=NULL, radius,
                     digits=3,
                     do.hist = TRUE, rm.hist = TRUE,
                     log = TRUE ,...)
{
  #takens <- takens[!is.na(takens)]
  xxrqa <- rqa(takens=takens,radius=radius)
  xxrqa$radius <- radius
  id <- attr(takens,"id")
  if (is.null(id)) id <- deparse(substitute(takens))
  xxrqa$id<- id
  xxrqa$time.lag <- attr(takens,"time.lag")
  cat(id, " n:", dim(takens)[1], " Dim:", dim(takens)[2], "\n")
  xxrqa$n <- dim(takens)[1]
  xxrqa$dim <- dim(takens)[2]
  #str(xxrqa)
  #str(digits)
  #browser()
  cat(paste("Radius:", radius,
            " Recurrence coverage REC:", round(xxrqa$REC, digits),
            " log(REC)/log(R):",
            round(log(xxrqa$REC)/log(radius), digits), "\n"))
  xxrqa$logratio <- log(xxrqa$REC)/log(radius)
  cat(paste("Determinism:", round(xxrqa$DET, digits),
            " Laminarity:",round(xxrqa$LAM, digits), "\n"))
  cat(paste("DIV:", round(xxrqa$DIV, digits), "\n"))
  cat(paste("Trend:", round(xxrqa$TREND, digits),
            " Entropy:",round(xxrqa$ENTR, digits), "\n"))
  cat(paste("Diagonal lines max:", round(xxrqa$Lmax, digits),
            " Mean:",round(xxrqa$Lmean, digits),
            " Mean off main:",round(xxrqa$LmeanWithoutMain, digits), "\n"))
  cat(paste("Vertical lines max:", round(xxrqa$Vmax, digits),
            " Mean:",round(xxrqa$Vmean, digits), "\n"))
  # str(xxrqa[4:12])

  if (do.hist){
    if (log==TRUE) log<-"y"
    oldpar <- par(mfrow=c(2,1))

    xxrqa$diagonalHistogram[xxrqa$diagonalHistogram==0] <- NA # hack for log zero counts
    dh<- xxrqa$diagonalHistogram
    #if (log=="y") {dh <- dh+1}

    id <- attr(takens,"id"); if (is.null(id) ) id <- deparse(substitute(takens))
    pars <- paste("\n n=", dim(takens)[1], " Dim:",
                dim(takens)[2])
    lag<- attr(takens,"time.lag")
    if (!is.null(lag) && (lag !=1) ) pars <- paste(pars, " Lag:", lag)
    try(plot(dh, type="h", main=paste( id, " Diagonal:",
                                         " Radius: ",radius, " REC:", round(xxrqa$REC, digits)),
             xlab="length of diagonals",
             log = log, ...))
    #needs handling of nan, Inf.

    xxrqa$recurrenceRate[xxrqa$recurrenceRate==0] <- NA # hack for log zero counts
    drR<- xxrqa$recurrenceRate
    #if (log=="y") {drR <- drR+1}
  }
}

```

```
id <- attr(takens,"id"); if (is.null(id) ) id <- deparse(substitute(takens))
pars <- paste("\n n=", dim(takens)[1], " Dim:",
            dim(takens)[2])
lag<- attr(takens,"time.lag")
if (!is.null(lag) && (lag !=1) ) pars <- paste(pars, " Lag:", lag)
plot(drR, type="h",
      main=paste( id," Recurrence Rate",
                  pars," Radius: ",radius, " REC:", round(xxrqa$REC, digits)),
      xlab="distance to diagonal",
      #ylim=c(1,3),
      log = log, ...)
par(oldpar)
}

if (rm.hist) { xxrqa$recurrenceRate <- NULL; xxrqa$diagonalHistogram <- NULL }
invisible(xxrqa)
}
```

3. TEST SIGNALS

We set up a small series of test signals. Some synthetic test signals are introduced here. More test cases used later are the Geyser data set (Section 7 on page 54) and two examples of heart rate data sets (Section 9 on page 79 and Section 10 on page 101) from *library(rhrv)*. The Geyser data set gives an example of a bi-variate point process. The HRV data sets give real live point orocess examples

For convenience, some source code from other libraries is included to make this self-contained.

As a global constant, we set up the length of the series to be used for test signals.

```
#nsignal <- 256
nsignal <- 1024
#nsignal <- 4096
system.time.start <- proc.time()
```

For signal representation, we use a common layout.

```
plotsignal <- function(signal, main, ylab) {
  #! alpha level should depend on expected number of overlaps

  if (missing(ylab)) { ylab <- deparse(substitute(signal)) }

  par(mfrow = c(1, 2))
  plot(signal,
       main = "", xlab = "index", ylab = ylab,
       col = rgb(0, 0, 1, 0.3), pch = 20)

  plot(signal, type = "l",
       main = "", xlab = "index", ylab = ylab,
       col = rgb(0, 0, 0, 0.4))
  points(signal,
         col = rgb(0, 0, 1, 0.3), pch = 20)
  if (missing(main)) { main = deparse(substitute(signal)) }
  title(main = paste("signal and linear interpolation\n", main),
        outer = TRUE, line = -2, cex.main = 1.2)
}
```

3.1. Sinus.

```
sin10 <- function(n=nsignal) {sin( (1:n)/n* 2*pi*10)}
plotsignal(sin10())
```

See Figure 2 on the next page.

3.2. Uniform Random Numbers.

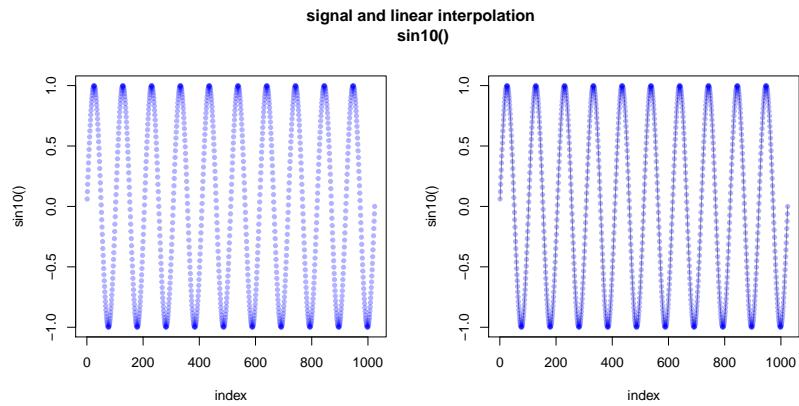


FIGURE 2. Test case: sin10. Signal and linear interpolation.

```
unif <- function(n=nsignal) {runif(n)}
xunif<-unif()
plotsignal(xunif)
```

See Figure 3,

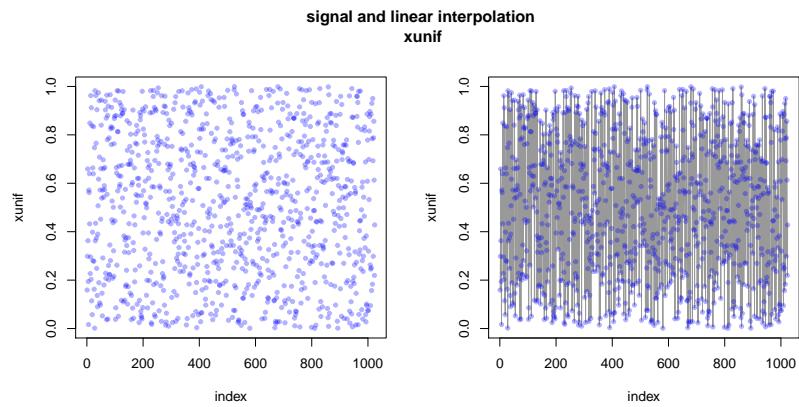


FIGURE 3. Test case: unif - uniform random numbers. Signal and linear interpolation.

3.3. Chirp Signal.

```

chirp <- function(n=nsignal)      Input # this is copied from library(signal)
{signal.chirp <- function(t, f0 = 0, t1 = 1, f1 = 100,
                           form = c("linear", "quadratic", "logarithmic"),
                           phase = 0){

  form <- match.arg(form);  phase <- 2*pi*phase/360

  switch(form,
    "linear" = {
      a <- pi*(f1 - f0)/t1;          b <- 2*pi*f0
      cos(a*t^2 + b*t + phase)
    },
    "quadratic" = {
      a <- (2/3*pi*(f1-f0)/t1/t1);      b <- 2*pi*f0
      cos(a*t^3 + b*t + phase)
    },
    "logarithmic" = {
      a <- 2*pi * t1 / log(f1 - f0);      b <- 2*pi * f0
      x <- (f1-f0)^(1/t1)
      cos(a*x*t + b*t + phase)
    })
}

signal.chirp(seq(0, 0.6, len=nsignal))
}
plotsignal(chirp())

```

See Figure 4,

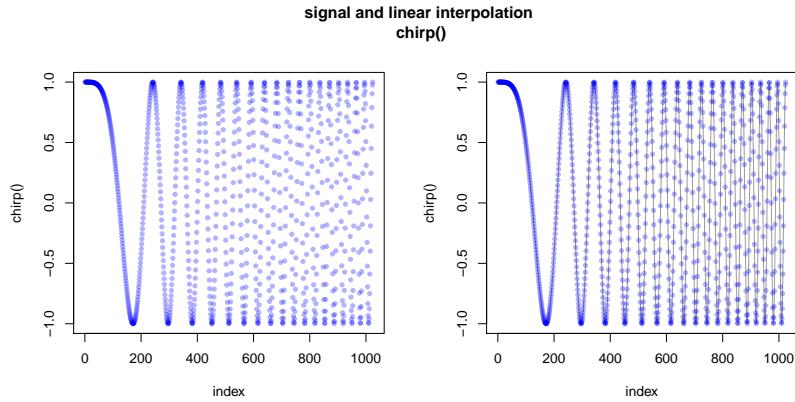


FIGURE 4. Test case: chirp signal. Signal and linear interpolation.

3.4. Doppler signal.

Input

```
doppler <- function(n=nsignal) {
  dopplersignal <- function(x) { sqrt(x*(1-x))* sin((2.1*pi)/(x+0.05)) }
  dopplersignal((1:nsignal)/nsignal)
}
plotsignal(doppler())
```

See Figure 5,

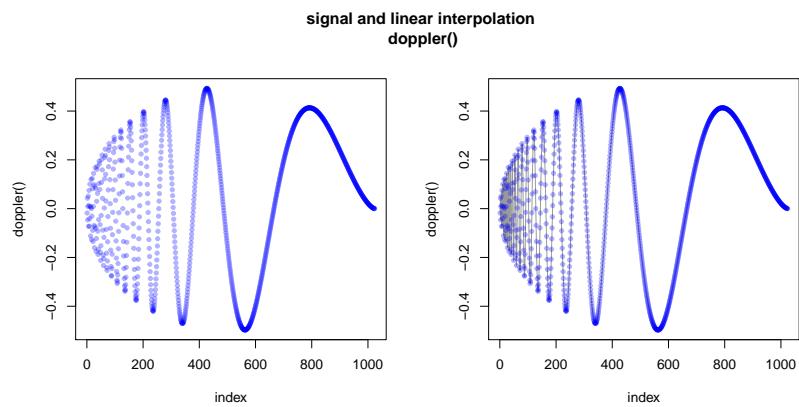


FIGURE 5. Test case: Doppler signal. Signal and linear interpolation.

4. NONLINEARTSERIES QUICK-START

Input

```
#suppressMessages(library('nonlinearTseries'))
library('plot3D')
# by default, the simulation creates a RGL plot of the system's phase space
```

4.1. Sinus.

Input

```
sinN <- sin10()
oldpar <- par(mfrow=c(1,2))
# tau delay estimation based on the autocorrelation function
tau.acf = timeLag(sinN, technique = "acf", do.plot = T,
main=paste("tau delay estimation based on acf\n","sin()"))
cat("tau.acf:",tau.acf)
```

Output

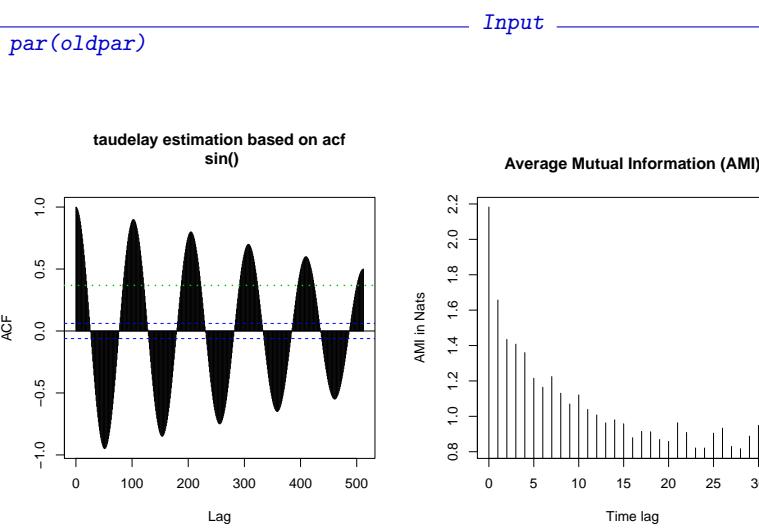
```
tau.acf: 20
```

Input

```
# tau delay estimation based on the mutual information function
tau.ami=NA
#try(tau.ami <- timeLag(sinN, technique = "ami", do.plot = T,
#main=paste("tau delay estimation based on ami\n","sin()"))
try(tau.ami <- timeLag(sinN, technique = "ami", do.plot = T, selection.method="first.minimum",
main=paste("tau delay estimation based on ami\n","sin()"))
cat("tau.ami:",tau.ami)
```

Output

```
tau.ami: 6
```



Note: fails. See Rnw source code.

4.2. Uniform Random Numbers.

Input

```
unifN <- unif()
oldpar <- par(mfrow=c(1,2))
# taudelay estimation based on the autocorrelation function
tau.acf = timeLag(unifN, technique = "acf", do.plot = T,
main=paste("taudelay estimation based on acf\n", deparse(substitute(x))))
cat("tau.acf:",tau.acf)
```

Output

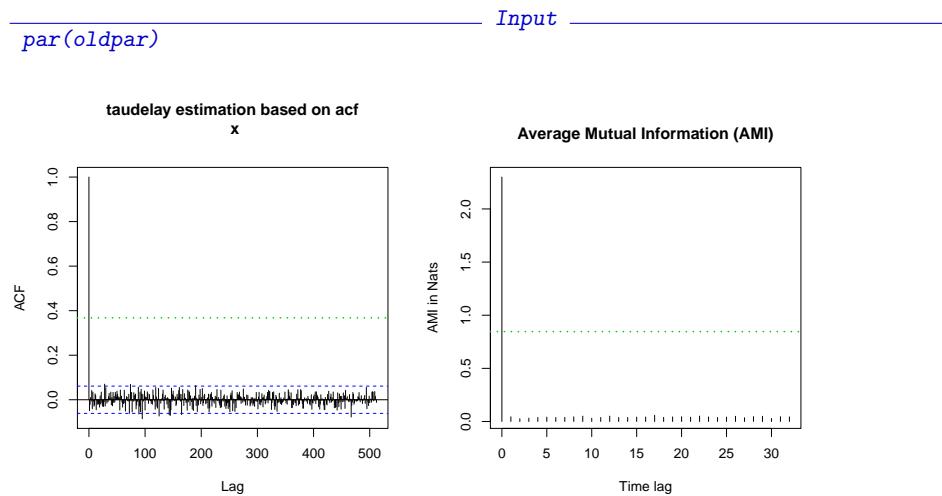
```
tau.acf: 1
```

Input

```
# tau delay estimation based on the mutual information function
tau.ami = timeLag(unifN, technique = "ami", do.plot = T,
main=paste("taudelay estimation based on ami\n", deparse(substitute(x))))
cat("tau.ami:",tau.ami)
```

Output

```
tau.ami: 1
```



Input

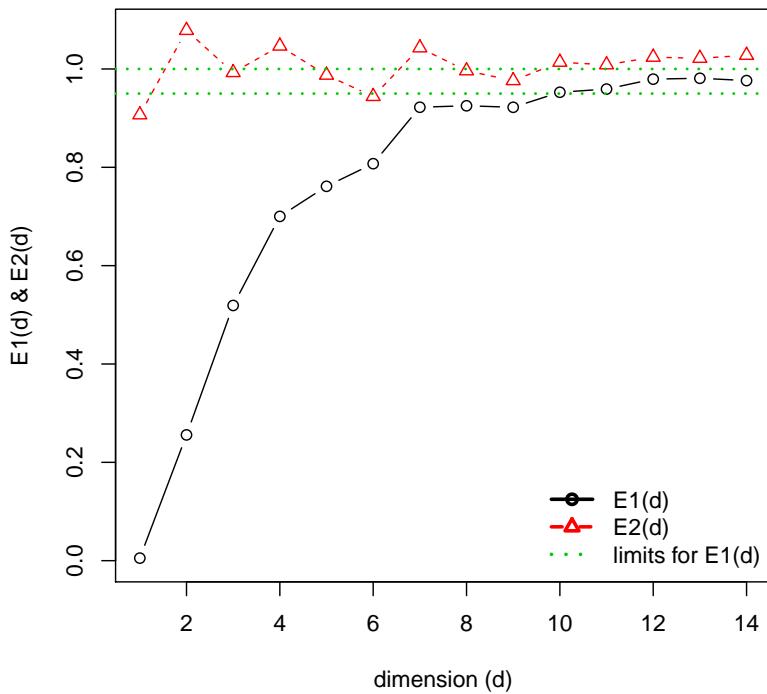
```
if (is.numeric(tau.ami)) {
emb.dim = estimateEmbeddingDim(unifN, time.lag = tau.ami,
max.embedding.dim = 15)} else {
emb.dim = estimateEmbeddingDim(unifN, time.lag = tau.acf,
max.embedding.dim = 15)}
cat("Estimated embedding dim:", emb.dim)
```

Output

```
Estimated embedding dim: 10
```

Input

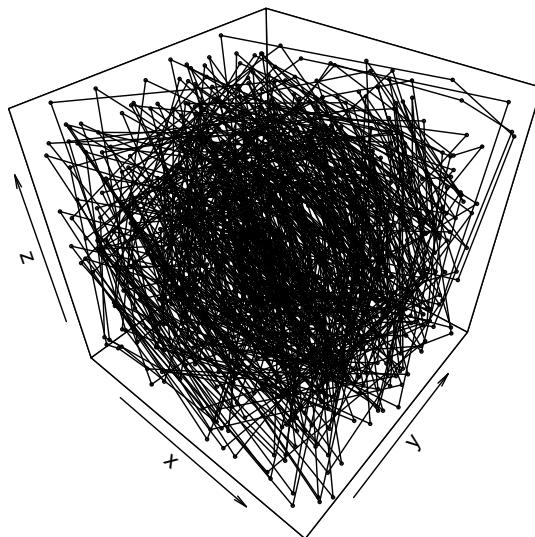
Computing the embedding dimension



Input

```
tak = buildTakens(unifN,embedding.dim = emb.dim, time.lag = tau.ami)
scatter3D(tak[,1], tak[,2], tak[,3],
main = paste("Reconstructed phase space",deparse(substitute(time.series))),
col = 1, type="o",cex = 0.3)
```

Reconstructed phase space time.series



4.3. Chirp.

Input

```
chirpN <- chirp()
oldpar <- par(mfrow=c(1,2))
# taudelay estimation based on the autocorrelation function
tau.acf = timeLag(chirpN, technique = "acf", do.plot = T,
main=paste("acf\n",deparse(substitute(x))))
cat("tau.acf:",tau.acf)
```

Output

```
tau.acf: 11
```

Input

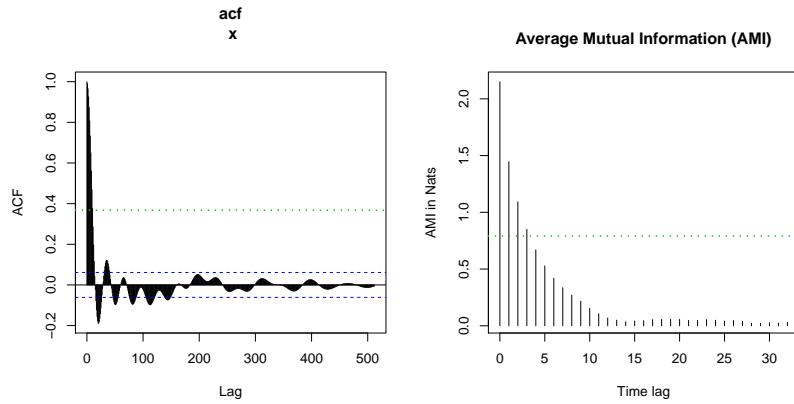
```
# taudelay estimation based on the mutual information function
tau.ami = timeLag(chirpN, technique = "ami", do.plot = T,
main=paste("ami\n",deparse(substitute(x))))
cat("tau.ami:",tau.ami)
```

Output

```
tau.ami: 4
```

Input

```
par(oldpar)
```



Input

```

if (is.numeric(tau.ami)) {
  emb.dim = estimateEmbeddingDim(chirpN, time.lag = tau.ami,
  max.embedding.dim = 15)} else {
  emb.dim = estimateEmbeddingDim(chirpN, time.lag = tau.acf,
  max.embedding.dim = 15)}
cat("Estimated embedding dim:", emb.dim)

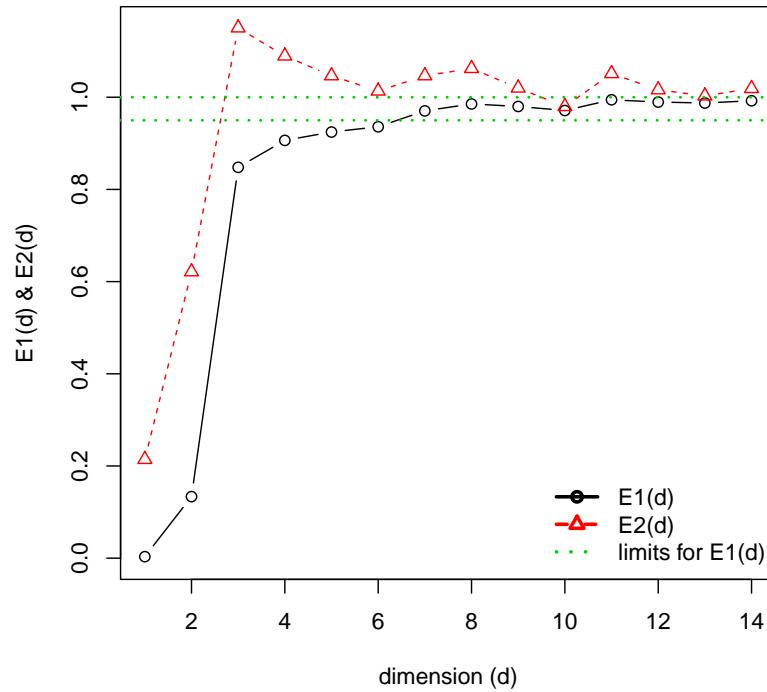
```

Output

Estimated embedding dim: 7

Input

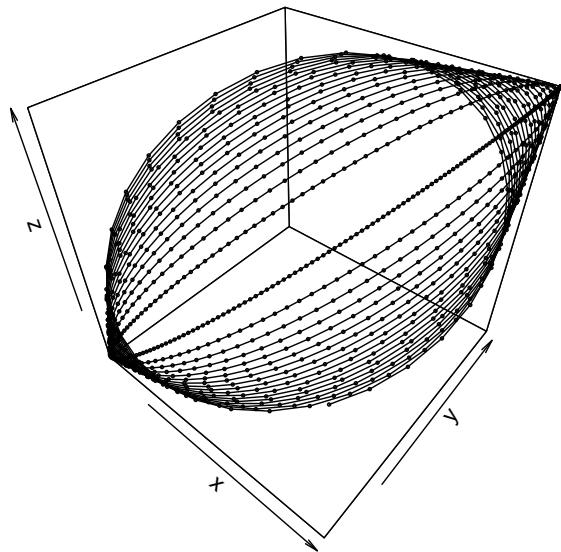
Computing the embedding dimension



Input

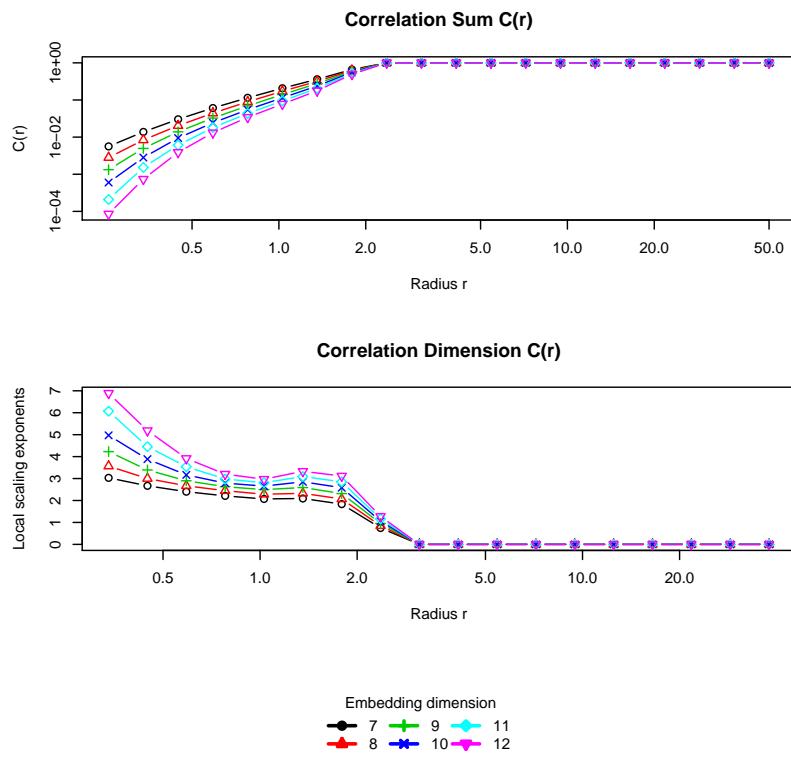
```
tak = buildTakens(chirpN,embedding.dim = emb.dim, time.lag = tau.ami)
scatter3D(tak[,1], tak[,2], tak[,3],
main = paste("Reconstructed phase space\n", "Chirp"),
col = 1, type="o", cex = 0.3)
```

**Reconstructed phase space
Chirp**



Input

```
cd = corrDim(chirpN,
min.embedding.dim = emb.dim,
max.embedding.dim = emb.dim + 5,
time.lag = tau.ami,
min.radius = 0.001, max.radius = 50,
n.points.radius = 40,
do.plot=FALSE)
plot(cd)
```



Input

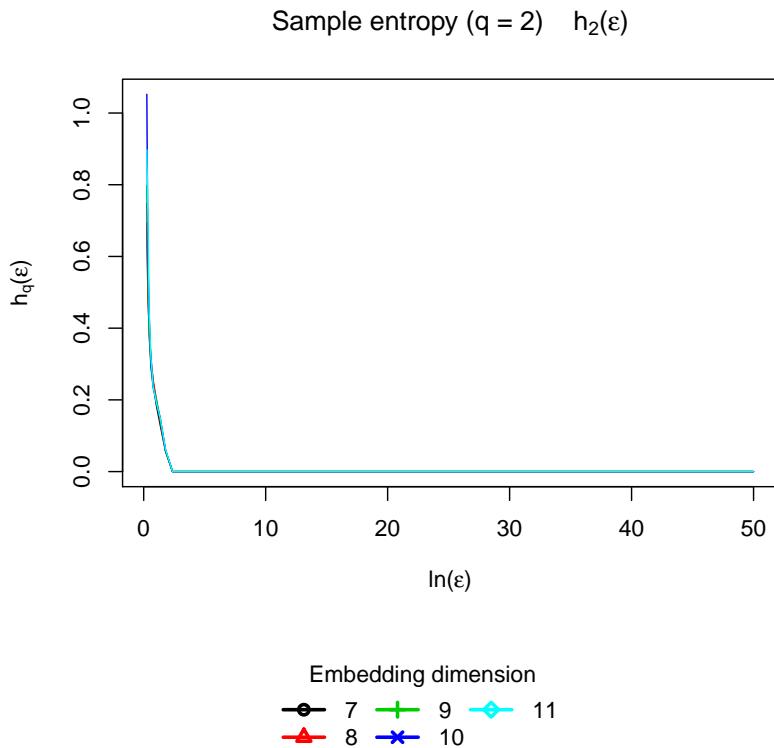
```
oldpar <- par(mfrow=c(1,2))
se = sampleEntropy(cd, do.plot =T)
se.est = estimate(se, do.plot = T,
regression.range = c(8,15))
cat("Sample entropy estimate: ", mean(se.est), "\n")
```

Output

```
Sample entropy estimate: 0
```

Input

```
par(oldpar)
```



Input

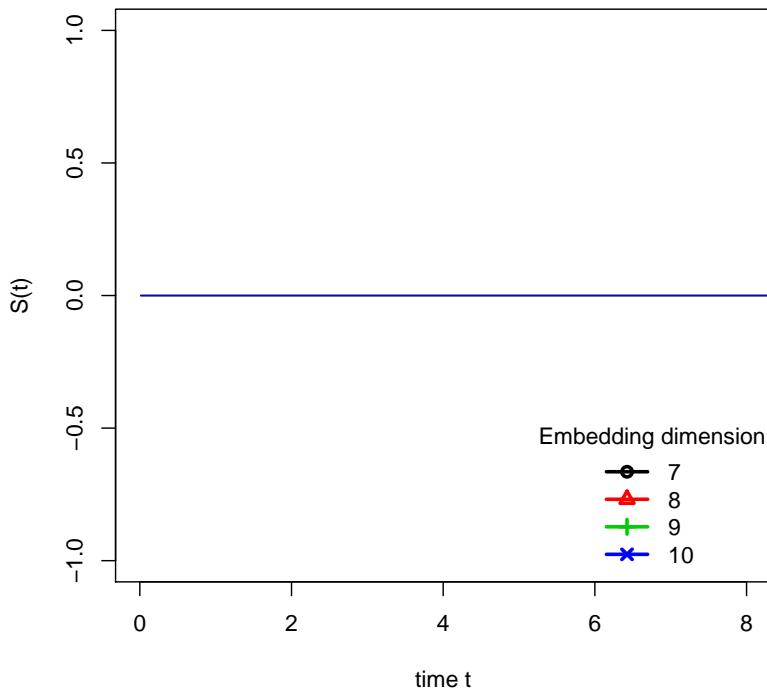
```
#sampling.period = diff(lor$time)[1]
ml = maxLyapunov(chirpN,
sampling.period=0.01,
min.embedding.dim = emb.dim,
max.embedding.dim = emb.dim + 3,
time.lag = tau.ami,
radius=1,
max.time.steps=1000,
do.plot=FALSE)
plot(ml,type="l", xlim = c(0,8))
ml.est = estimate(ml, regression.range = c(0,3),
do.plot = T,type="l")
#cat("expected: 0.906 estimate:", ml.est, "\n")
cat("estimate:", ml.est, "\n")
```

Output

```
estimate: 0
```

Input

Estimating maximal Lyapunov exponent

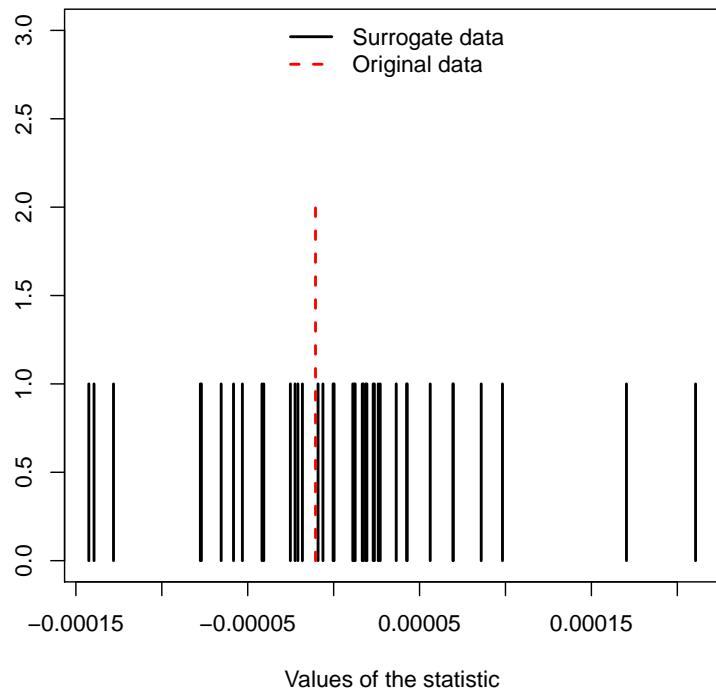


Input

```

st = surrogateTest(chirpN,significance = 0.05,one.sided = F,
FUN = timeAsymmetry, do.plot=F)
## Computing statistics
##
## Null Hypothesis: Data comes from a linear stochastic process
## Reject Null hypothesis:
## Original data's stat is significant larger than surrogates' stats
plot(st)

```

Surrogate data testing

4.4. Doppler.

Input

```
dopplerN <- doppler()
oldpar <- par(mfrow=c(1,2))
# tau delay estimation based on the autocorrelation function
tau.acf = timeLag(dopplerN, technique = "acf", do.plot = T,
main=paste("acf\n",deparse(substitute(x))))
cat("tau.acf:",tau.acf)
```

Output

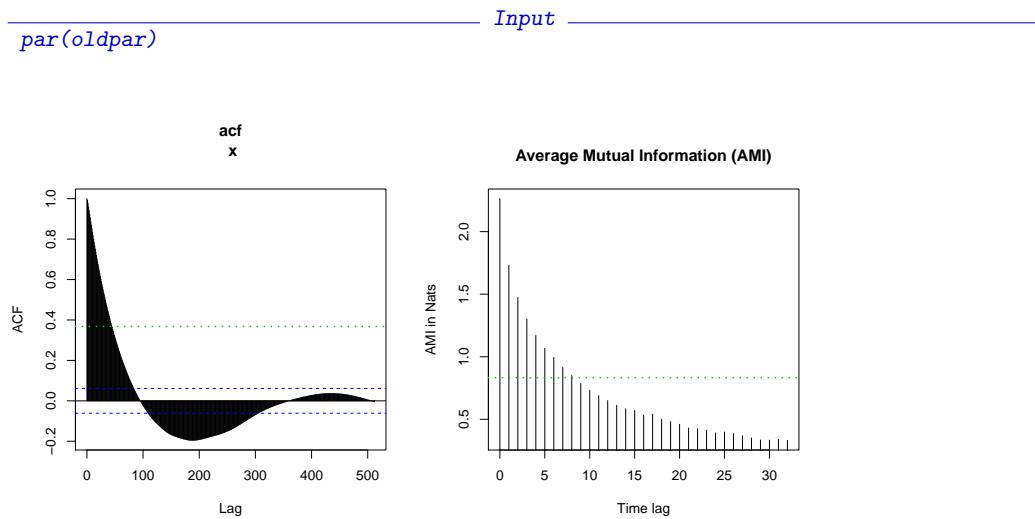
```
tau.acf: 45
```

Input

```
# tau delay estimation based on the mutual information function
tau.ami = timeLag(dopplerN, technique = "ami", do.plot = T,
main=paste("ami\n",deparse(substitute(x))))
cat("tau.ami:",tau.ami)
```

Output

```
tau.ami: 9
```



Input

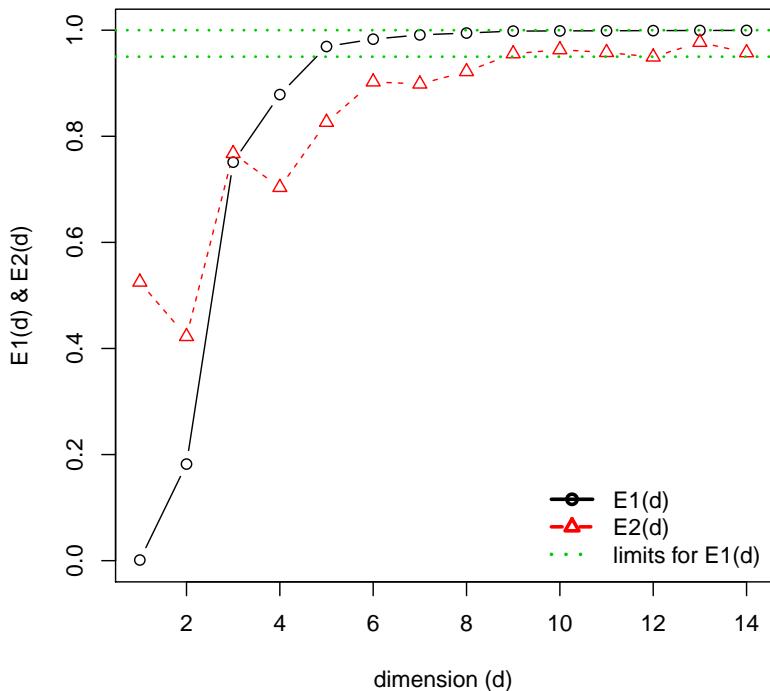
```
if (is.numeric(tau.ami)) {
emb.dim = estimateEmbeddingDim(dopplerN, time.lag = tau.ami,
max.embedding.dim = 15)} else {
emb.dim = estimateEmbeddingDim(dopplerN, time.lag = tau.acf,
max.embedding.dim = 15)}
cat("Estimated embedding dim:", emb.dim)
```

Output

```
Estimated embedding dim: 5
```

Input

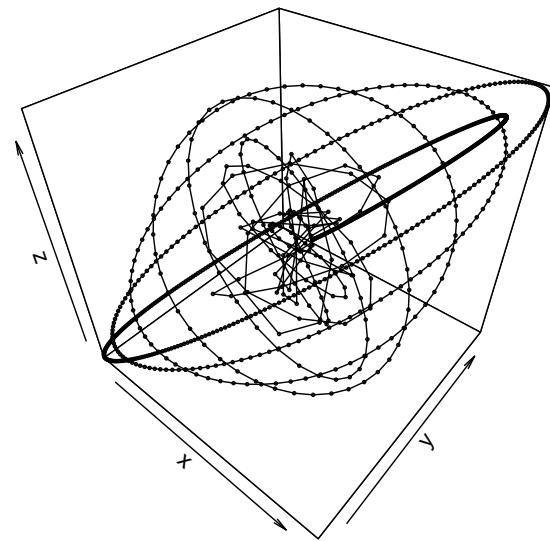
Computing the embedding dimension



Input

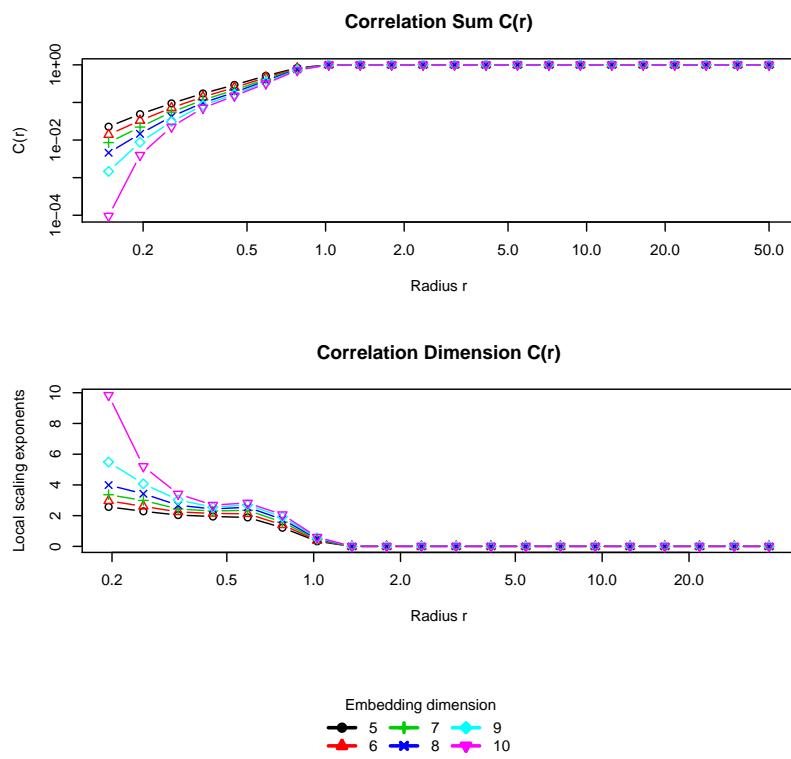
```
tak = buildTakens(dopplerN,embedding.dim = emb.dim, time.lag = tau.ami)
scatter3D(tak[,1], tak[,2], tak[,3],
main = "Reconstructed phase space \n doppler" ,
col = 1, type="o",cex = 0.3)
```

Reconstructed phase space doppler



Input

```
cd = corrDim(dopplerN,  
min.embedding.dim = emb.dim,  
max.embedding.dim = emb.dim + 5,  
time.lag = tau.ami,  
min.radius = 0.001, max.radius = 50,  
n.points.radius = 40,  
do.plot=FALSE)  
plot(cd)
```



Input

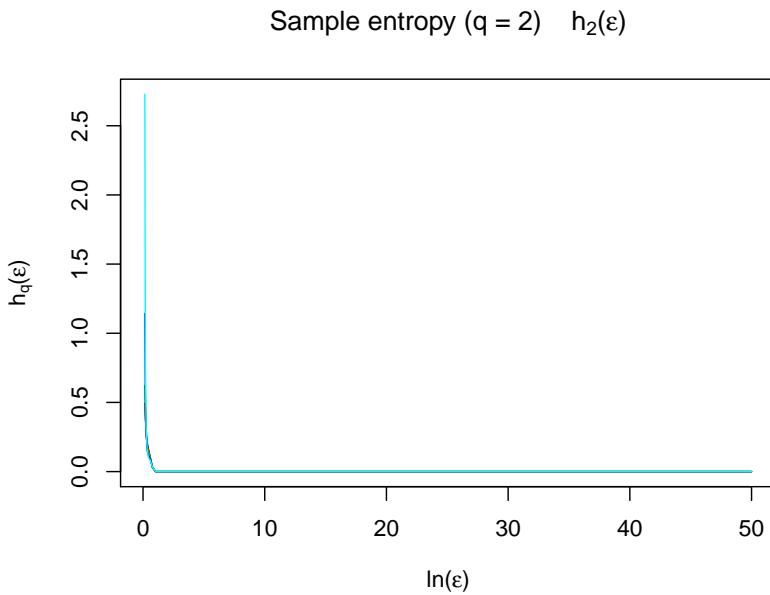
```
oldpar <- par(mfrow=c(1,2))
se = sampleEntropy(cd, do.plot = T)
se.est = estimate(se, do.plot = T,
regression.range = c(8,15))
cat("Sample entropy estimate: ", mean(se.est), "\n")
```

Output

```
Sample entropy estimate: 0
```

Input

```
par(oldpar)
```



Embedding dimension

	5		7		9
	6		8		

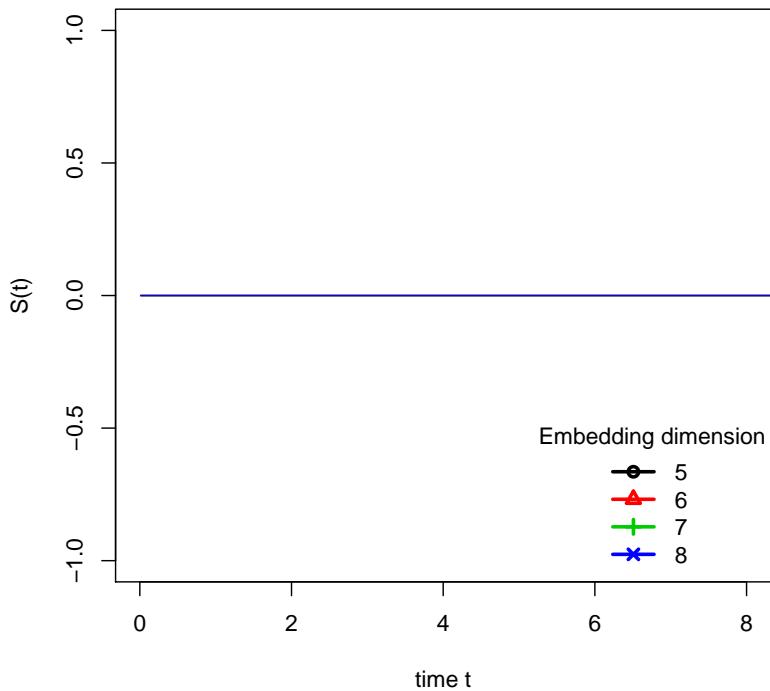
Input

```
#sampling.period = diff(lor$time)[1]
ml = maxLyapunov(dopplerN,
sampling.period=0.01,
min.embedding.dim = emb.dim,
max.embedding.dim = emb.dim + 3,
time.lag = tau.ami,
radius=1,
max.time.steps=1000,
do.plot=FALSE)
plot(ml,type="l", xlim = c(0,8))
ml.est = estimate(ml, regression.range = c(0,3),
do.plot = T,type="l")
#cat("expected: 0.906 estimate:", ml.est, "\n")
cat("estimate:", ml.est, "\n")
```

Output

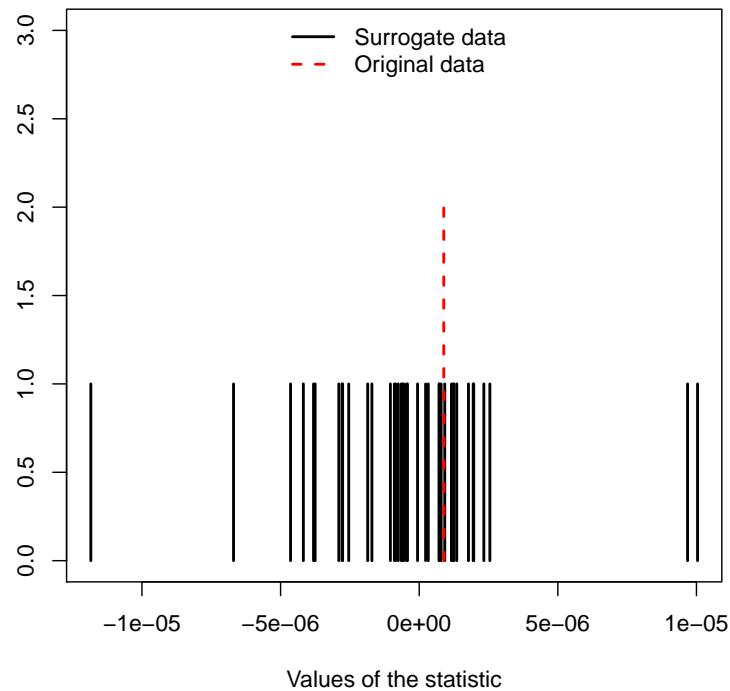
```
estimate: 0
```

Input

Estimating maximal Lyapunov exponent

Input

```
st = surrogateTest(dopplerN,significance = 0.05,one.sided = F,
FUN = timeAsymmetry, do.plot=F)
## Computing statistics
##
## Null Hypothesis: Data comes from a linear stochastic process
## Reject Null hypothesis:
## Original data's stat is significant larger than surrogates' stats
plot(st)
```

Surrogate data testing

5. TAKENS' STATES FOR TEST SIGNALS

```
Input
sintakens <- local.buildTakens(time.series=sin10(),
                                 embedding.dim=4, time.lag=1)
statepairs(sintakens) #4
```

See Figure 6.

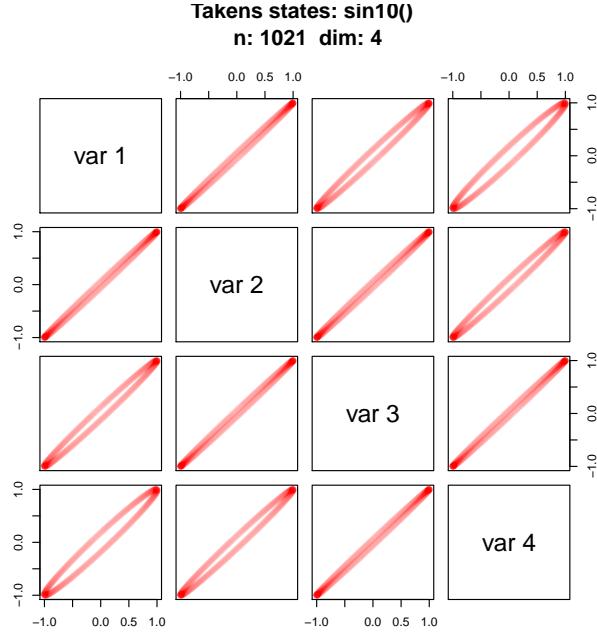


FIGURE 6. Takens states. Test case: sinus. Note that $2 - dim$ marginal views of 1-dimensional circles in d space generally appear as ellipses. Time used: 0.667 sec.

The states only catch the local behaviour, where “local” depends on the sampling rate and the variation of the signal. For the sinus signal, we get a better picture if we subsample the signal.

```
Input
sintakenslag16 <- local.buildTakens(time.series=sin10(),
                                       embedding.dim=4, time.lag=16)
statepairs(sintakenslag16) #4
```

See Figure 7 on the following page.

```
Input
statepairs(sintakens, nooverlap=TRUE) #dim=4
```

See Figure 8 on the next page.

```
Input
statecplot(sintakens) #4
```

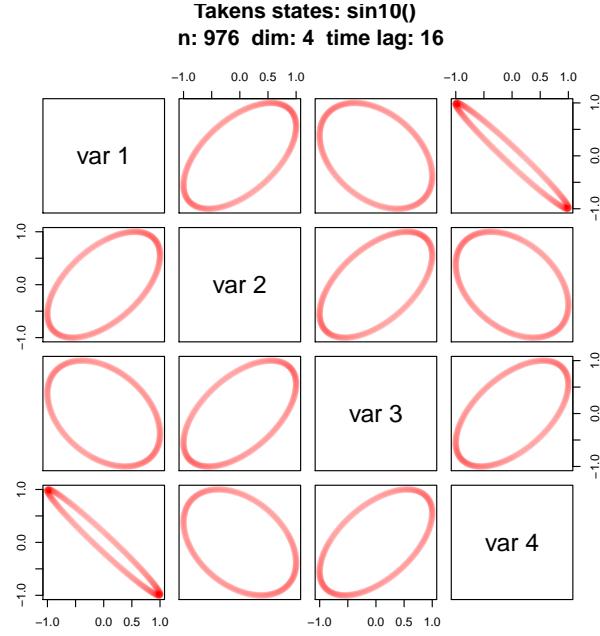


FIGURE 7. Takens states. Test case: sinus at time lag 16. Note that 2–dim marginal views of 1-dimensional circles in d space generally appear as ellipses. Time used: 0.633 sec.

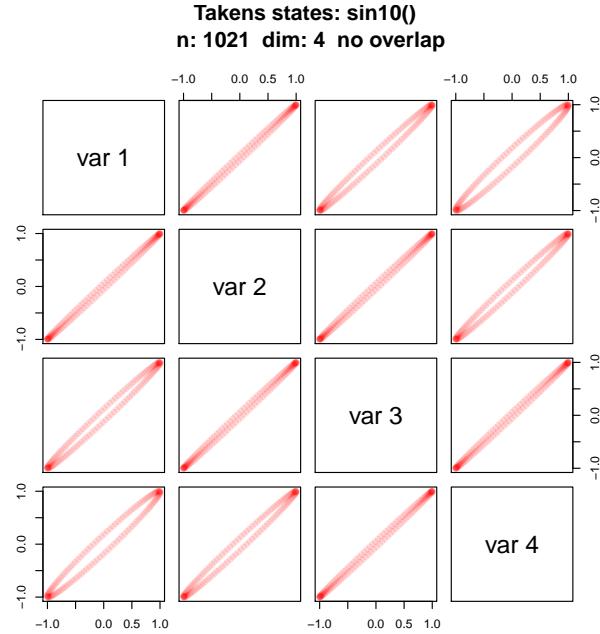


FIGURE 8. Takens states. Test case: sinus, no overlap. Note that 2–dim marginal views of 1-dimensional circles in d space generally appear as ellipses. Time used: 0.817 sec.

See Figure 9.

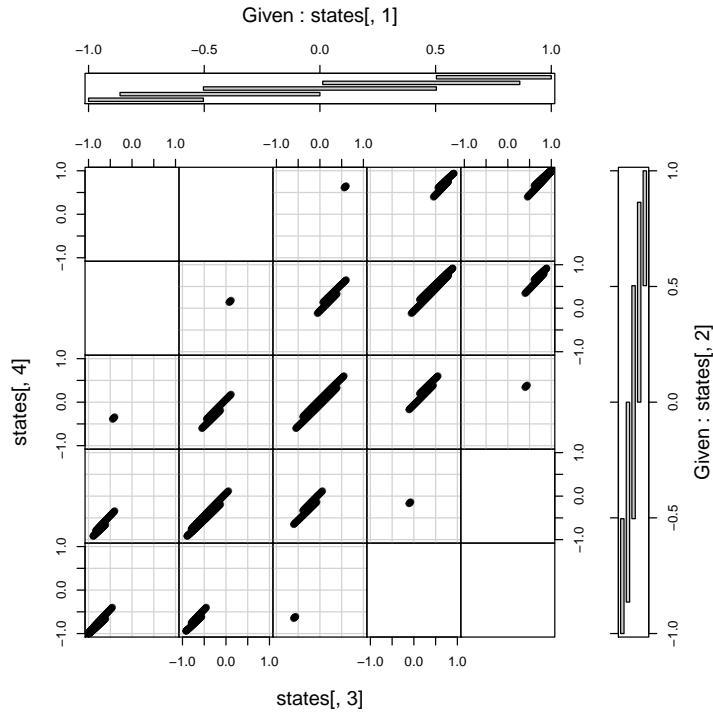


FIGURE 9. State coplot. Test case: sinus. Note that $2 - \dim$ marginal views of 1-dimensional circles in d space generally appear as ellipses. Time used: 0.235 sec.

Input

```
statecoplot(sintakenslag16) #4
```

See Figure 10 on the next page.

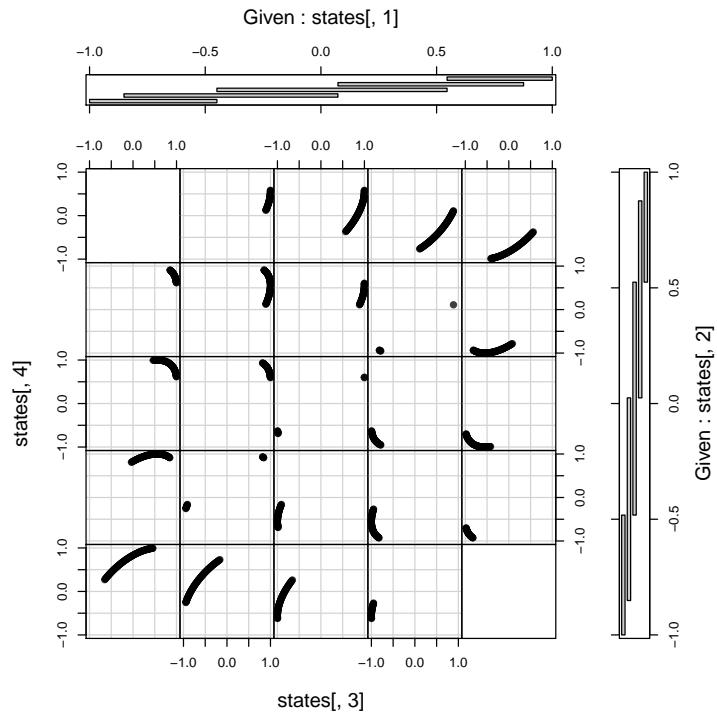


FIGURE 10. State coplot. Test case: sinus, time lag 16. Note that 2-dim marginal views of 1-dimensional circles in d space generally appear as ellipses. Time used: 0.173 sec.

```
Input
uniftakens <- local.buildTakens( time.series=xunif,
    embedding.dim=4, time.lag=1)
statepairs(uniftakens) #dim=4
```

See Figure 11.

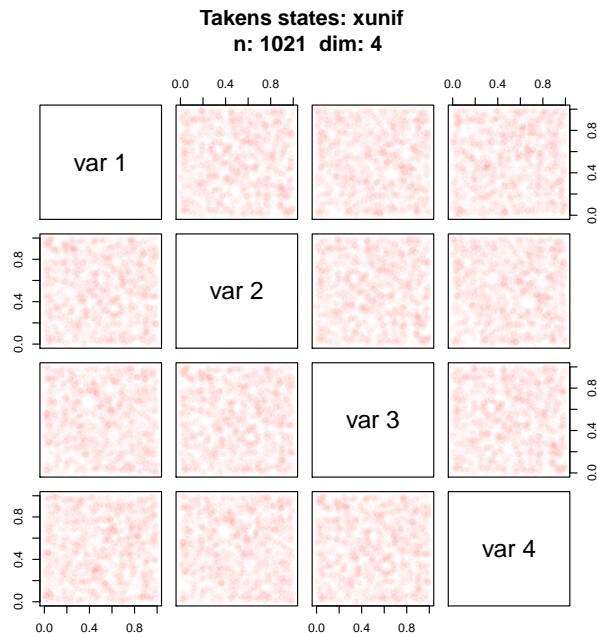


FIGURE 11. Takens states. Test case: uniform random numbers. Time used: 0.638 sec.

```
Input
statecoplot(uniftakens) #dim=4
```

See Figure 12 on the next page.

```
Input
statepairs(uniftakens, nooverlap=TRUE) #dim=4
```

See Figure 13 on the following page.

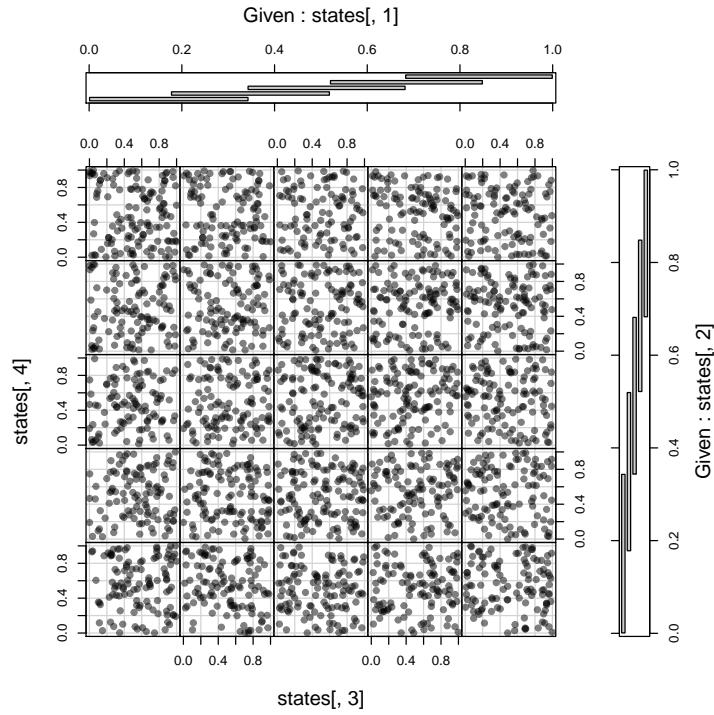


FIGURE 12. State coplot. Test case: uniform random numbers. Time used: 0.871 sec.

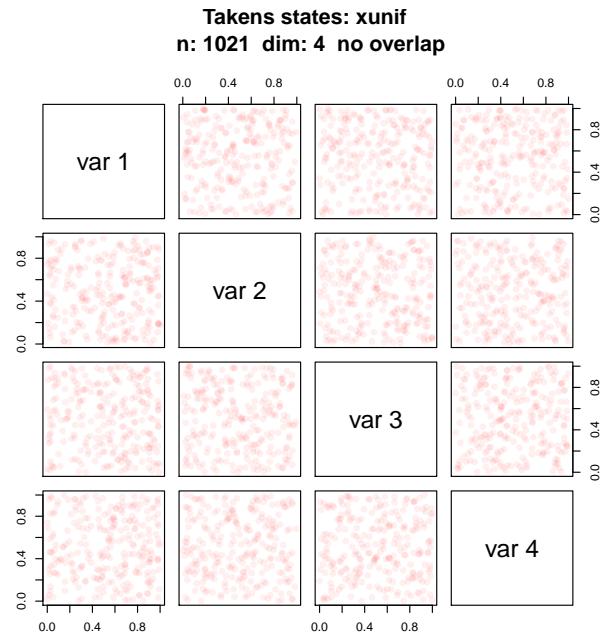


FIGURE 13. Takens states. Test case: uniform random numbers. Time used: 1.092 sec.

```
Input
chirptakens <- local.buildTakens( time.series=chirp(),
    embedding.dim=4, time.lag=1)
statepairs(chirptakens) #dim=4
```

See Figure 14.

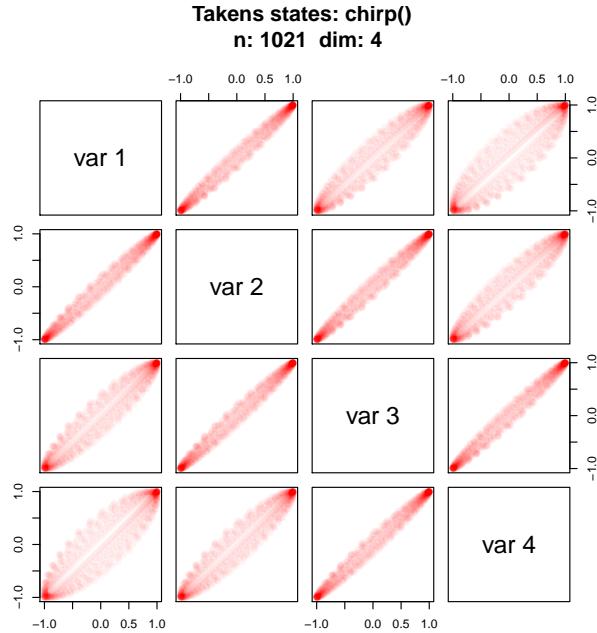


FIGURE 14. Takens states. Test case: chirp signal. Time used: 0.667 sec.

```
Input
statecplot(chirptakens) #dim=4
```

See Figure 15 on the following page.

```
Input
statepairs(chirptakens, nooverlap=TRUE) #dim=4
```

See Figure 16 on the next page.

```
Input
dopplertakens <- local.buildTakens(time.series=doppler(),
    embedding.dim=4, time.lag=1)
statepairs(dopplertakens) #4
```

See Figure 17 on page 41.

The states only catch the local behaviour, where “local” depends on the sampling rate and the variation of the signal. For the doppler signal, we get a better picture if we subsample the signal.

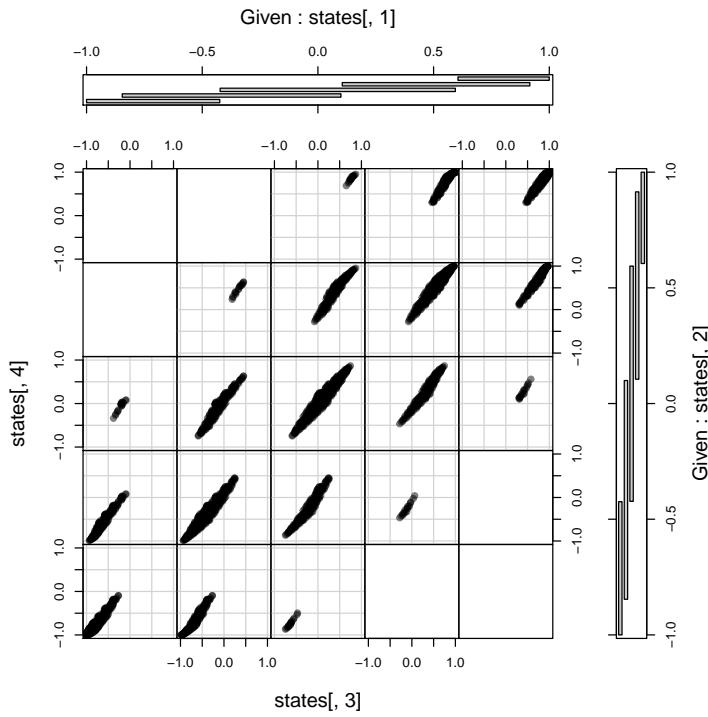


FIGURE 15. State coplot. Test case: chirp signal. Time used: 1.013 sec.

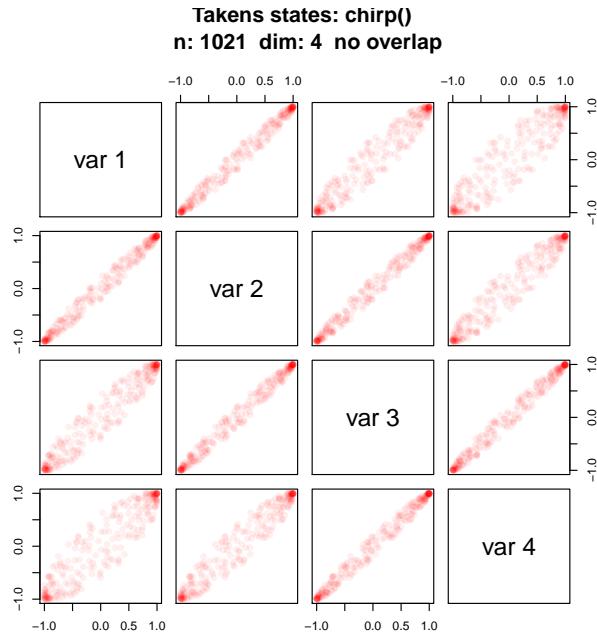


FIGURE 16. Takens states. Test case: chirp signal. Time used: 1.229 sec-

Input

```
dopplertakenslag16 <- local.buildTakens(time.series=doppler(),
  embedding.dim=4, time.lag=16)
statepairs(dopplertakenslag16) #4
```

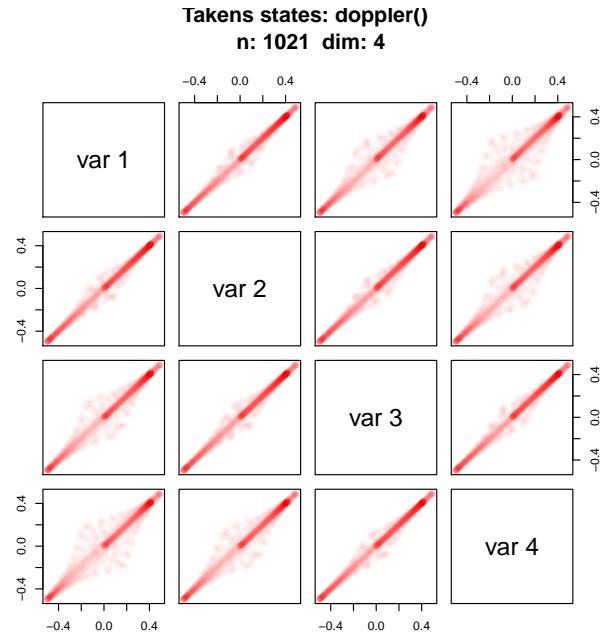


FIGURE 17. Takens states. Test case: Doppler. Note that $2 - \dim$ marginal views of 1-dimensional circles in d space generally appear as ellipses. Time used: 0.635 sec.

See Figure 18.

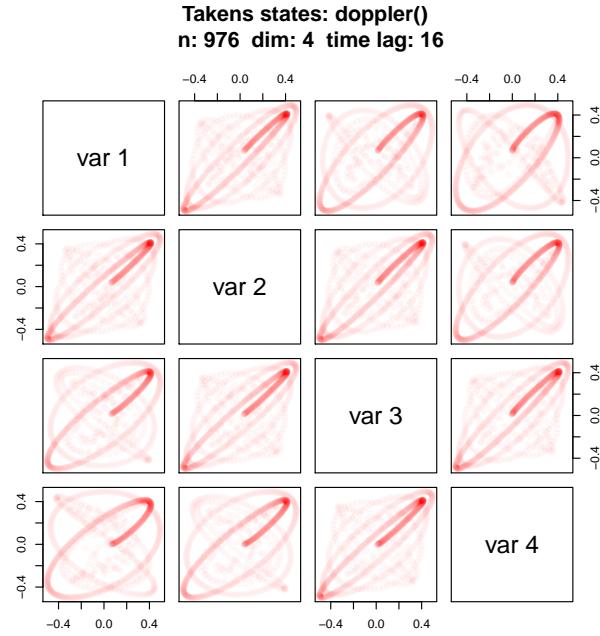


FIGURE 18. Takens states. Test case: doppler at time lag 16. Note that $2 - \dim$ marginal views of 1-dimensional circles in d space generally appear as ellipses. Time used: 0.633 sec.

Input

```
statepairs(dopplertakens, nooverlap=TRUE) #dim=4
```

See Figure 19.

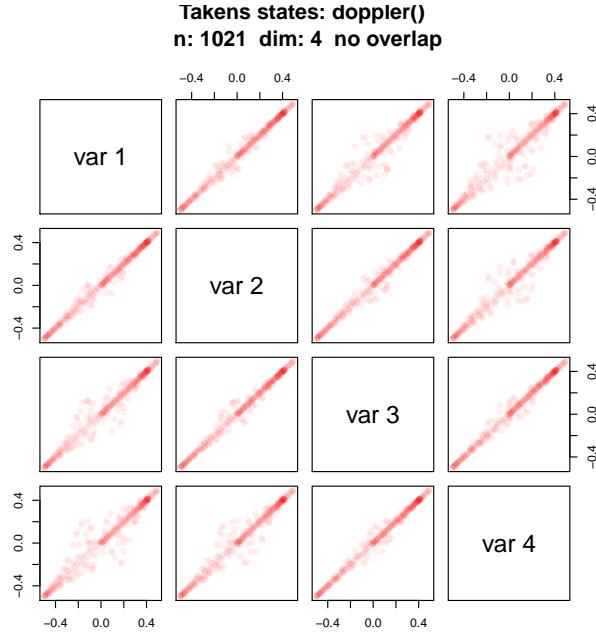


FIGURE 19. Takens states. Test case: doppler, no overlap. Note that 2-dim marginal views of 1-dimensional circles in d space generally appear as ellipses. Time used: 0.831 sec.

Input

```
statecoplot(dopplertakens) #4
```

See Figure 20 on the next page.

Input

```
statecoplot(dopplertakenslag16) #4
```

See Figure 21 on the facing page.

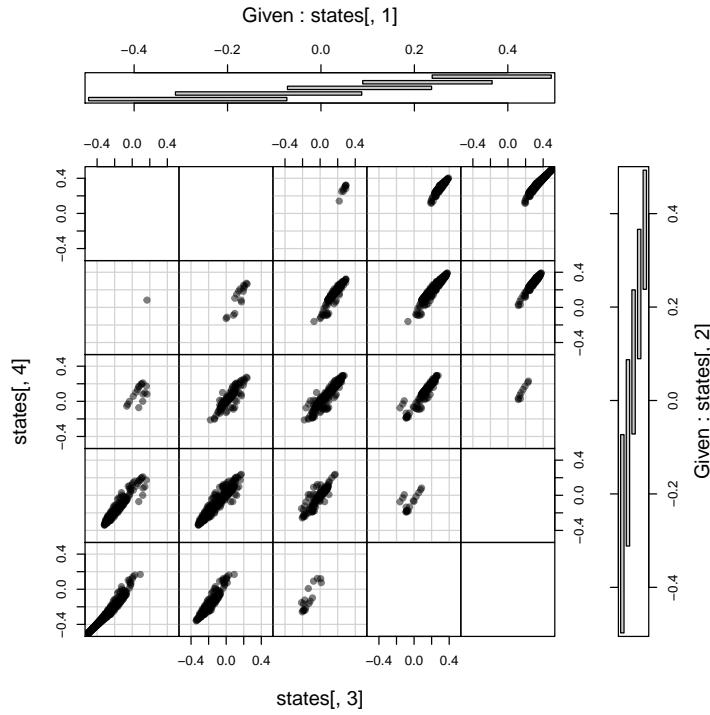


FIGURE 20. State coplot. Test case: Doppler. Note that 2-dim marginal views of 1-dimensional circles in d space generally appear as ellipses. Time used: 0.207 sec.

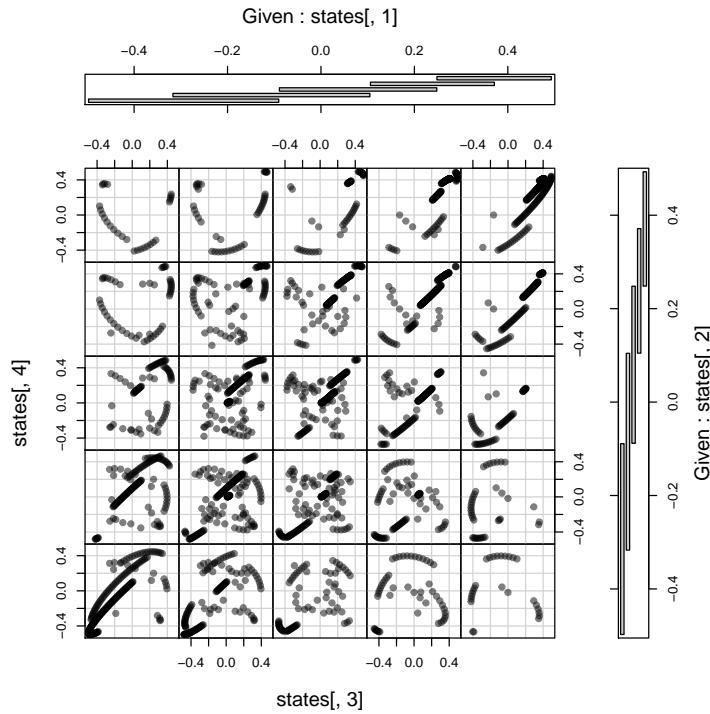


FIGURE 21. State coplot. Test case: Doppler, time lag 16. Note that 2-dim marginal views of 1-dimensional circles in d space generally appear as ellipses. Time used: 0.193 sec.

6. RECURRENCE PLOTS FOR TEST SIGNALS

6.0.1. Sinus Recurrence Plots.

```

Input
sin10neighs <- local.findAllNeighbours(sintakens, radius=0.8)
save(sin10neighs, file="sin10neighs.Rdata")
# load(file="sin10neighs.RData")
local.recurrencePlotAux(sin10neighs, dim=dim(sintakens)[2], radius=0.8)
```

See Figure 22.

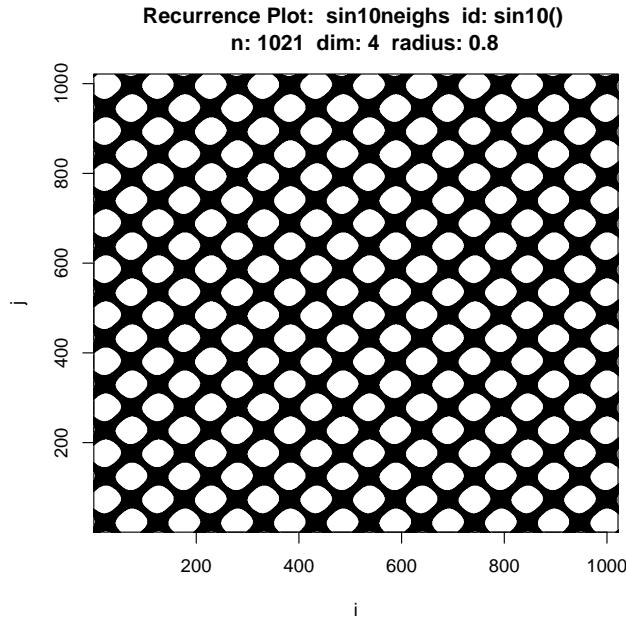


FIGURE 22. Recurrence plot. Test case: sinus. Time used: 2.044 sec.

```

Input
sin10rqa <- showrqa(sintakens, radius=0.8, log=TRUE)

Output
sin10() n: 1021 Dim: 4
Radius: 0.8 Recurrence coverage REC: 0.496 log(REC)/log(R): 3.143
Determinism: 1 Laminarity: 1
DIV: 0.001
Trend: 0 Entropy: 3.213
Diagonal lines max: 1020 Mean: 32.712 Mean off main: 32.65
Vertical lines max: 66 Mean: 41.479
```

RQA Test case: sinus. Radius=0.8.. Time used: 3.061 sec. For graphical ouput, see Figure 23 on the facing page.

```

Input
sin10lag16neighs <- local.findAllNeighbours(sintakenslag16, radius=0.2)
save(sin10lag16neighs, file="sin10lag16neighs.Rdata")
```

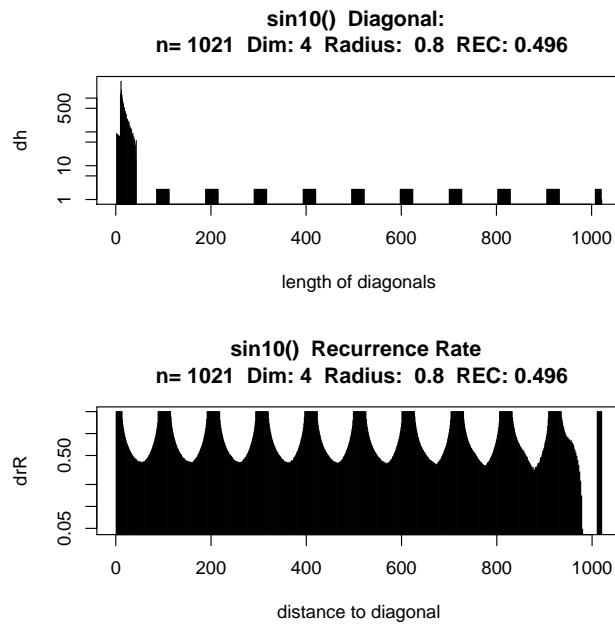


FIGURE 23. RQA. Test case: sinus. Radius=0.8., 0.64

```
# load(file="sin10lag16neighs.RData")
local.recurrencePlotAux(sin10lag16neighs, dim=4, radius=0.2)
```

See Figure 24.

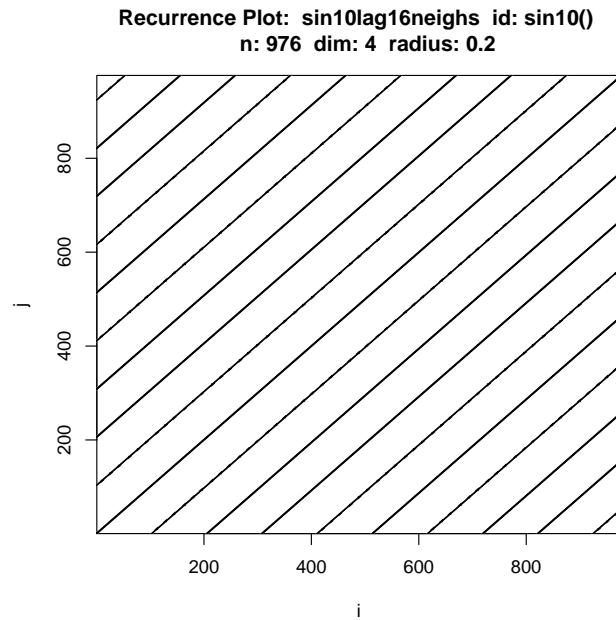


FIGURE 24. Recurrence plot. Test case: sinus curve, time lag 16. Time used: 3.807 sec.

Input

```
sin10lag16rqa <- showrqa(sintakenslag16, radius=0.2)
```

Output

```
sin10() n: 976 Dim: 4
Radius: 0.2 Recurrence coverage REC: 0.067 log(REC)/log(R): 1.683
Determinism: 0.999 Laminarity: 1
DIV: 0.001
Trend: 0 Entropy: 2.316
Diagonal lines max: 975 Mean: 124.503 Mean off main: 122.827
Vertical lines max: 8 Mean: 6.774
```

RQA Test case: sinus curve, time lag 16. Time used: 3.95 sec. For graphical output, see Figure 25.

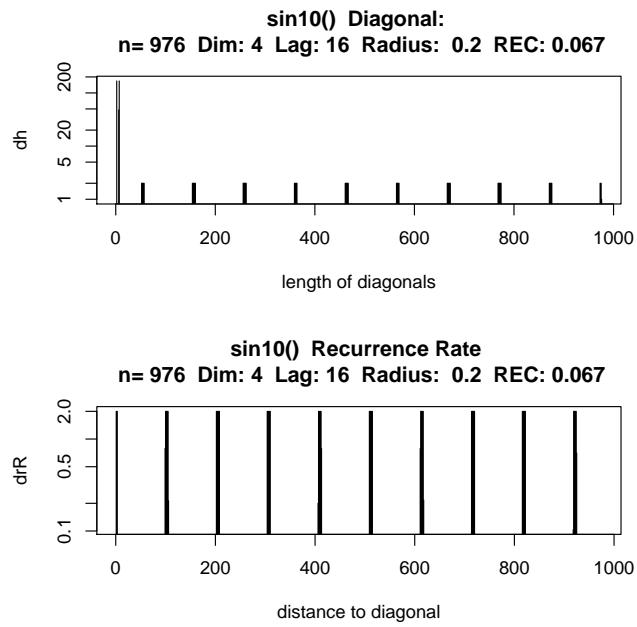


FIGURE 25. RQA. Test case: sinus curve, time lag 16, 0.64

6.0.2. Uniform Random Numbers Recurrence Plots.

Input

```
unifneighs <- local.findAllNeighbours(uniftakens, radius=0.6)#0.4
save(unifneighs, file="unifneighs.RData")
# load(file="unifneighs.RData")
local.recurrencePlotAux(unifneighs, radius=0.6)
```

See Figure 26.

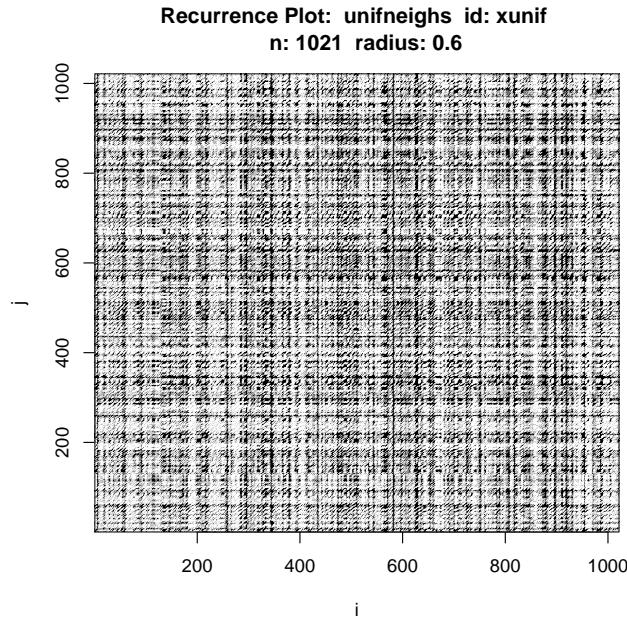


FIGURE 26. Recurrence plot. Test case: uniform random numbers. Time used: 1.983 sec.

Input

```
showrqa(uniftakens, radius=0.6, log=TRUE)
```

Output

```
xunif n: 1021 Dim: 4
Radius: 0.6 Recurrence coverage REC: 0.491 log(REC)/log(R): 1.392
Determinism: 0.973 Laminarity: 0.785
DIV: 0.017
Trend: 0 Entropy: 2.716
Diagonal lines max: 60 Mean: 7.092 Mean off main: 7.078
Vertical lines max: 1021 Mean: 3.867
```

RQA Test case: uniform random numbers, radius=0.6. Time used: 2.717 sec. For graphical output, see Figure 27 on the following page.

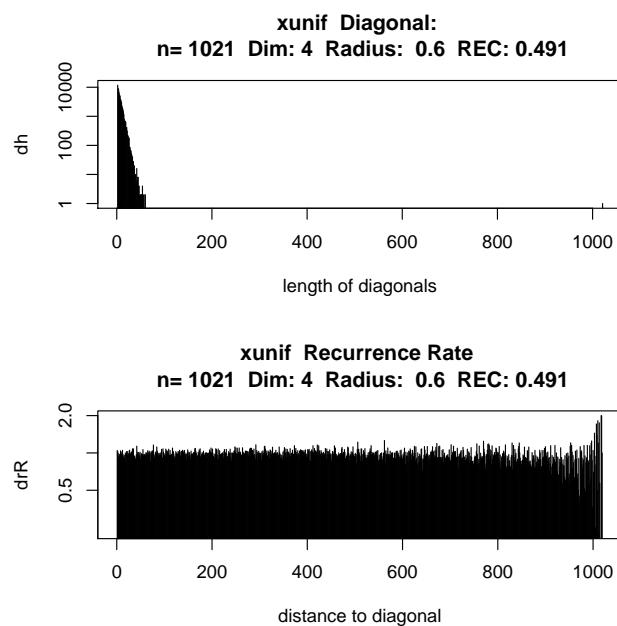


FIGURE 27. RQA. Test case: uniform random numbers, radius=0.6, 0.64

6.0.3. Chirp Signal Recurrence Plots.

Input

```
chirpnear <- local.findAllNeighbours(chirptakens, radius=0.6)
save(chirpnear, file="chirpnear.RData")
# load(file="chirpnear.RData")
local.recurrencePlotAux(chirpnear, radius=0.6)
```

See Figure 28.

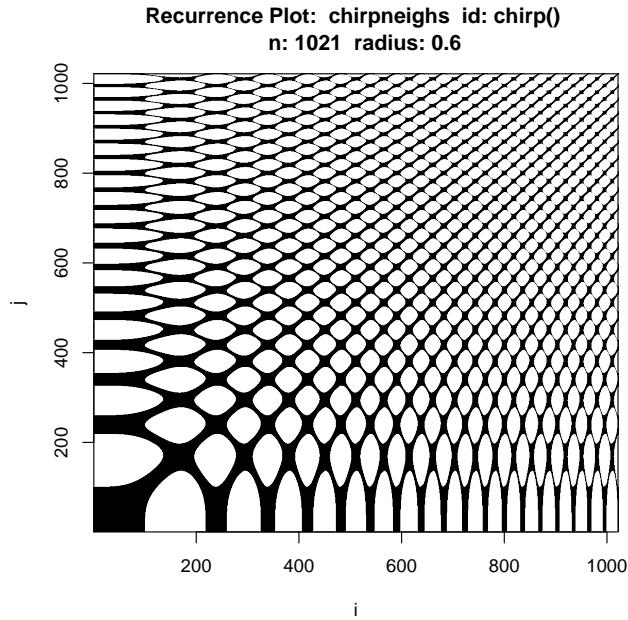


FIGURE 28. Recurrence plot. Test case: chirp signal. Time used: 1.054 sec.

Input

```
showrqa(chirptakens, radius=0.6)
```

Output

```
chirp() n: 1021 Dim: 4
Radius: 0.6 Recurrence coverage REC: 0.341 log(REC)/log(R): 2.108
Determinism: 0.988 Laminarity: 0.998
DIV: 0.001
Trend: 0 Entropy: 3.254
Diagonal lines max: 1020 Mean: 12.496 Mean off main: 12.46
Vertical lines max: 125 Mean: 14.721
```

RQA Test case: chirp signal. Time used: 1.489 sec. For graphical output, see Figure 29 on the following page.

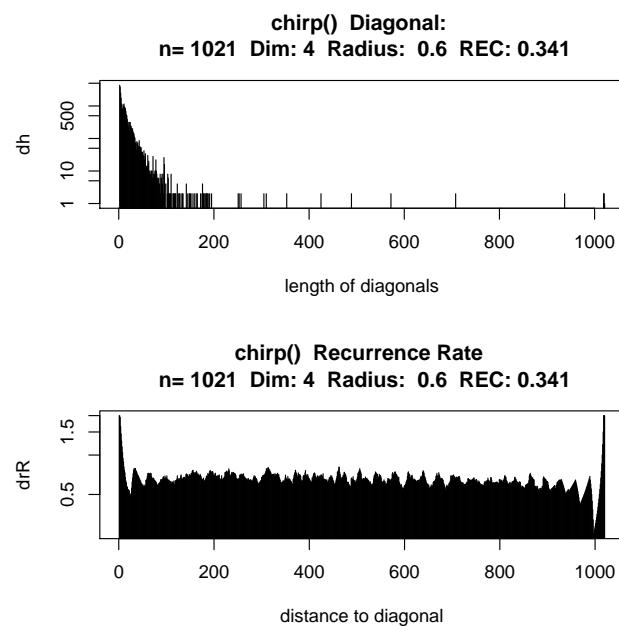


FIGURE 29. RQA. Test case: chirp signal, 0.64

6.0.4. *Doppler Recurrence Plots.*

Input

```
dopplerneighs <- local.findAllNeighbours(dopplertakens, radius=0.2)
save(dopplerneighs, file="dopplerneighs.Rdata")
```

Input

```
load(file="dopplerneighs.RData")
local.recurrencePlotAux(dopplerneighs, dim=4, radius=0.2)
```

See Figure 30.

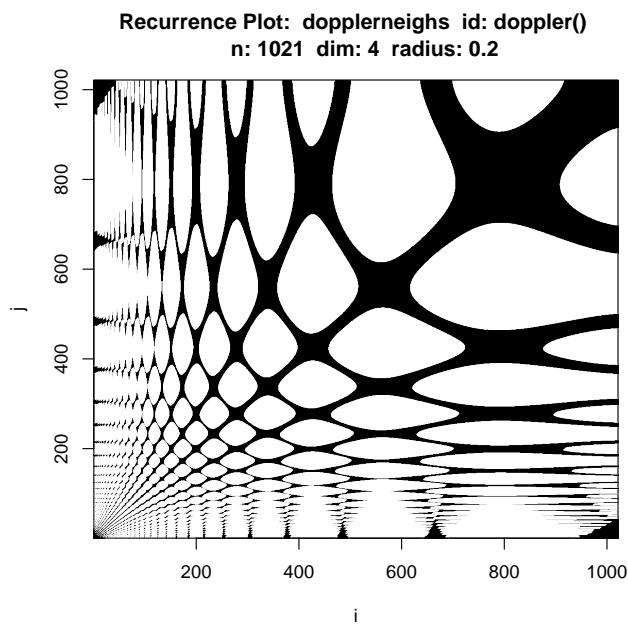


FIGURE 30. Recurrence plot. Test case: Doppler. Time used: 0.933 sec.

Input

```
showrqa(dopplertakens, radius=0.2)
```

Output

```
doppler() n: 1021 Dim: 4
Radius: 0.2 Recurrence coverage REC: 0.299 log(REC)/log(R): 0.75
Determinism: 0.991 Laminarity: 0.995
DIV: 0.001
Trend: 0 Entropy: 3.445
Diagonal lines max: 1020 Mean: 17.496 Mean off main: 17.439
Vertical lines max: 329 Mean: 24.835
```

RQA Test case: Doppler. Time used: 0.472 sec. For graphical ouput, see Figure 31 on the following page.

Input

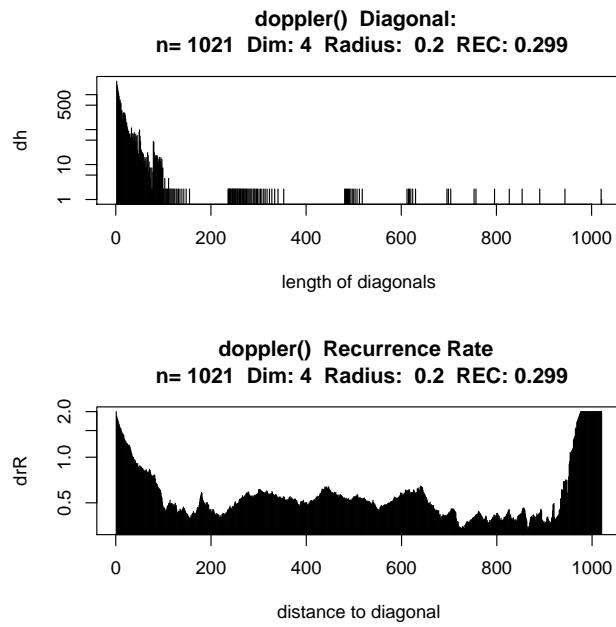


FIGURE 31. RQA. Test case: Doppler, 0.64

```
dopplerlag16neighs <- local.findAllNeighbours(dopplertakenslag16, radius=0.2)
save(dopplerlag16neighs, file="dopplerlag16neighs.Rdata")
# load(file="dopplerlag16neighs.RData")
local.recurrencePlotAux(dopplerlag16neighs, dim=4, radius=0.2)
```

See Figure 32.

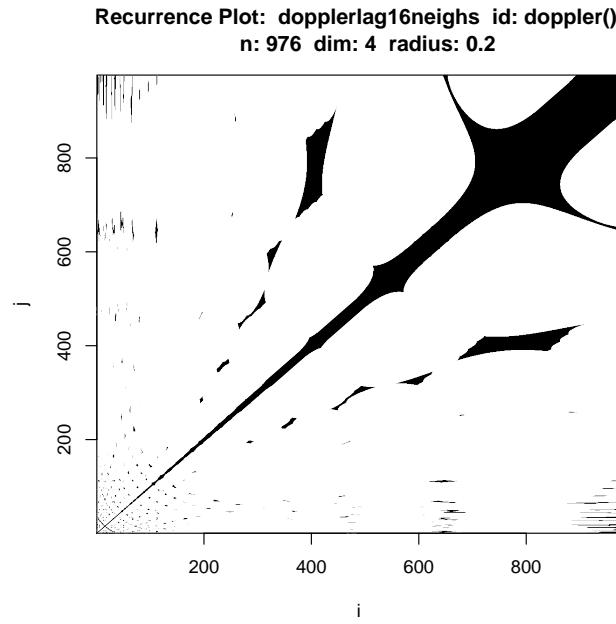


FIGURE 32. Recurrence plot. Test case: Doppler. Time used: 0.662 sec.

Input

```
showrqa(dopplertakenslag16, radius=0.2)
```

Output

```
doppler() n: 976 Dim: 4
Radius: 0.2 Recurrence coverage REC: 0.098 log(REC)/log(R): 1.443
Determinism: 0.98 Laminarity: 0.989
DIV: 0.001
Trend: 0 Entropy: 2.815
Diagonal lines max: 975 Mean: 28.978 Mean off main: 28.678
Vertical lines max: 256 Mean: 31.539
```

RQA RQA. Test case: Doppler. Time used: 0.957 sec. For graphical ouput, see Figure 33.

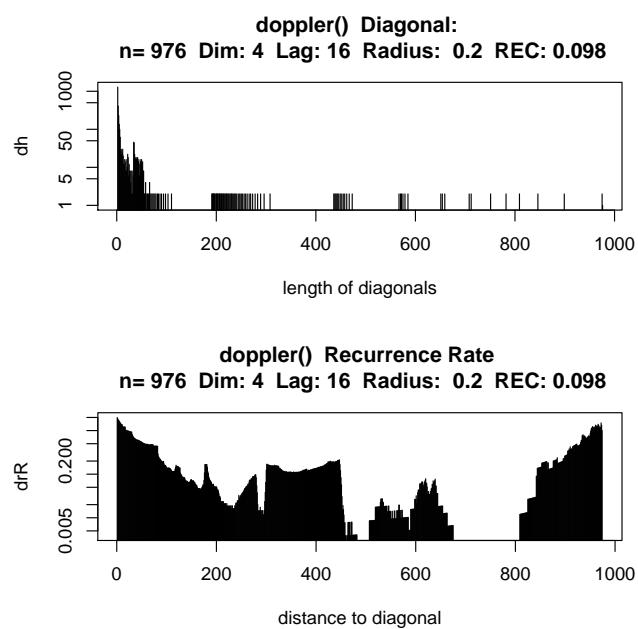


FIGURE 33. RQA. RQA. Test case: Doppler, 0.64

ToDo: double check:
 MASS:::geyser should be used, not faithful

7. GEYSER EXAMPLE AND BIVARIATE RECURRENCE PLOTS

7.1. Paired sequences. This is a classical data set with a two dimensional structure. Components are *duration* and *waiting*.

More specific the Geyser is a marked point process, with points marked as duration and waiting.

Decomposing it, we get two sequences, duration and waiting. Both sequences have (at least) bi-modal structures - a peculiarity of this data set. The main application problem is to predict waiting, based on the available information from the past.

Note for data analysis: The time to predict is the waiting time for the next eruption; so for prediction use a shifted sequence *waiting*[−1].

Note for data analysis: Some data are not recorded, but replaced by codes such as short, long. Handling of partially encoded data is required.

After decomposition, both sequences can be handled separately.

Input

```
try(detach("package:MASS" ), silent=TRUE)
try(detach(faithful), silent=TRUE)
try(detach(geyser), silent=TRUE)
library(MASS)
data(geyser)
attach(geyser)
```

Input

```
plotsignal(duration)
```

Input

```
plotsignal(waiting)
```

Time used: 0.174 sec. Signal components and linear interpolation. See Figure 34 on the next page.

Input

```
attach(geyser)
takens.duration4 <- buildTakens( time.series=duration, embedding.dim=4, time.lag=1)
takens.waiting4 <- buildTakens( time.series=waiting, embedding.dim=4, time.lag=1)
```

Time used: 0.184 sec.

Input

```
duration4rqa <- showrqa(takens.duration4, radius=0.8, log=TRUE)
```

Output

```
duration n: 296 Dim: 4
Radius: 0.8 Recurrence coverage REC: 0.112 log(REC)/log(R): 9.822
Determinism: 0.903 Laminarity: 0.076
DIV: 0.05
```

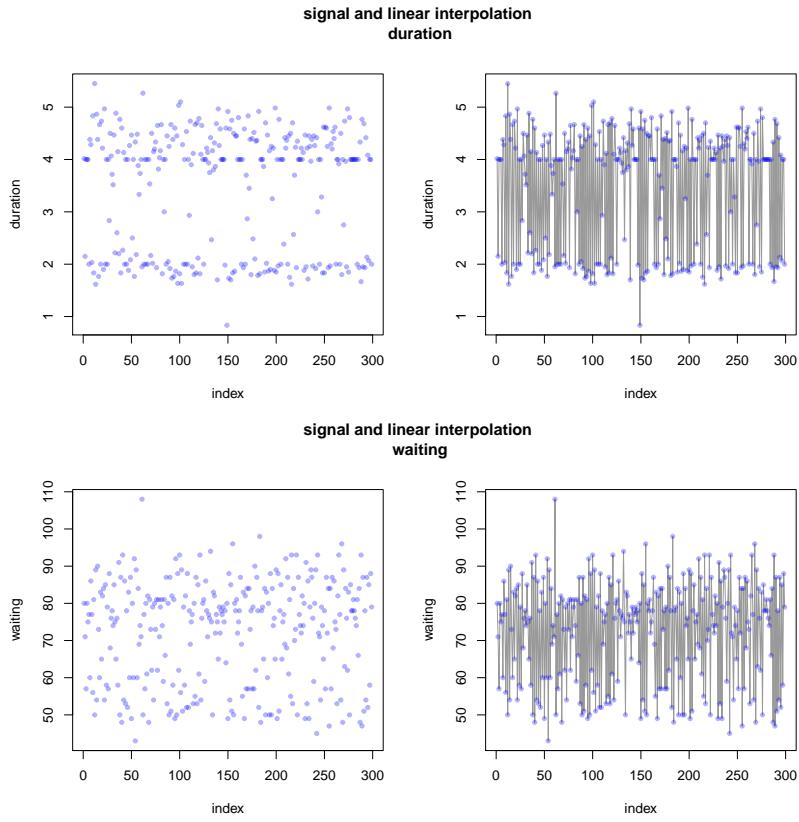


FIGURE 34. Example case: Old Faithful Geyser eruption durations and waiting time. Signals and linear interpolation. Time used: 0.175 sec.

```
Trend: 0 Entropy: 1.779
Diagonal lines max: 20 Mean: 3.919 Mean off main: 3.79
Vertical lines max: 5 Mean: 3.041
```

RQA Geyser duration. Radius=0.8.. Time used: 0.238 sec. For graphical ouput, see Figure 35 on the following page.

Input

```
waiting4rqa <- showrqa(takens.waiting4, radius=2.4, log=TRUE)
```

Output

```
waiting n: 296 Dim: 4
Radius: 2.4 Recurrence coverage REC: 0.004 log(REC)/log(R): -6.251
Determinism: 0.88 Laminarity: 0
DIV: 0.333
Trend: 0 Entropy: 0.859
Diagonal lines max: 3 Mean: 24.923 Mean off main: 2.333
Vertical lines max: 0 Mean: 0
```

RQA Geyser waiting. Radius=2.4.. Time used: 0.288 sec. For graphical ouput, see Figure 36 on the next page.

Input

```
statepairs(takens.duration4) #dim=4
```

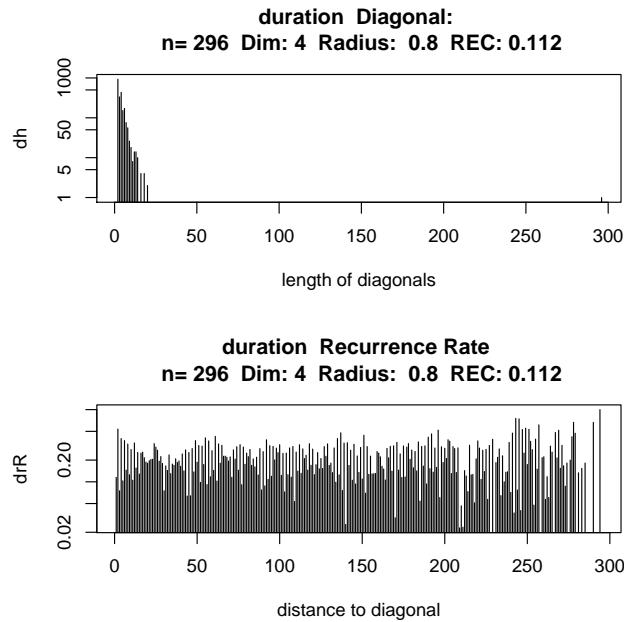


FIGURE 35. RQA. Geyser duration. Radius=0.8., 0.64

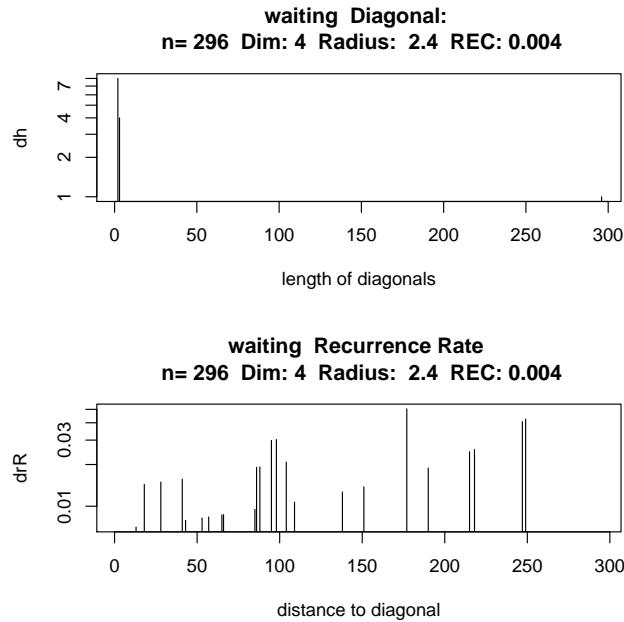


FIGURE 36. RQA. Geyser waiting. Radius=2.4., 0.64

Input

```
statepairs(takens.waiting4) #dim=4
```

Example case: Old Faithful Geyser eruption data. Time used: 0.716 sec. See Figure 38 on the facing page.

ToDo: use nooverlap ?

Input
`statecoplot(takens.duration4) #dim=4`

See Figure 37.

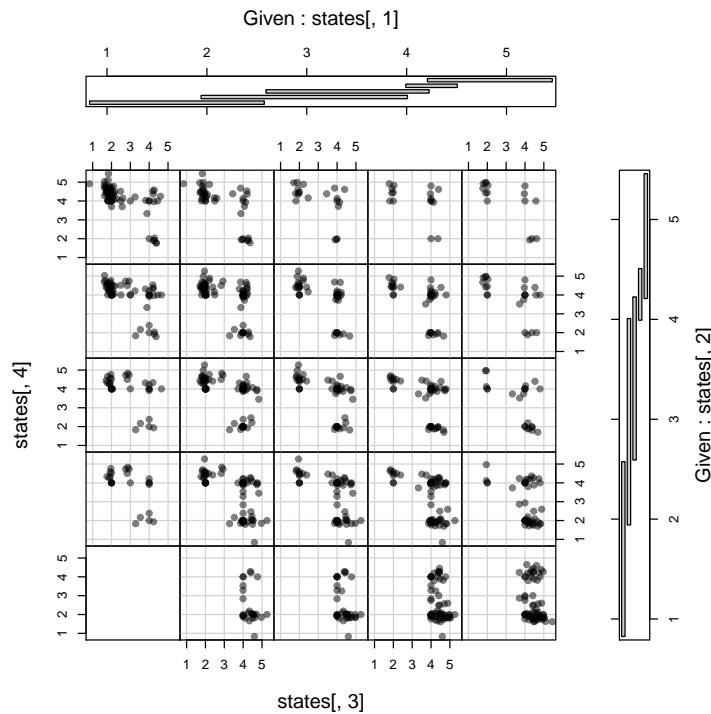


FIGURE 37. State coplot. Example case: Old Faithful Geyser eruption durations. Time used: 0.828 sec.

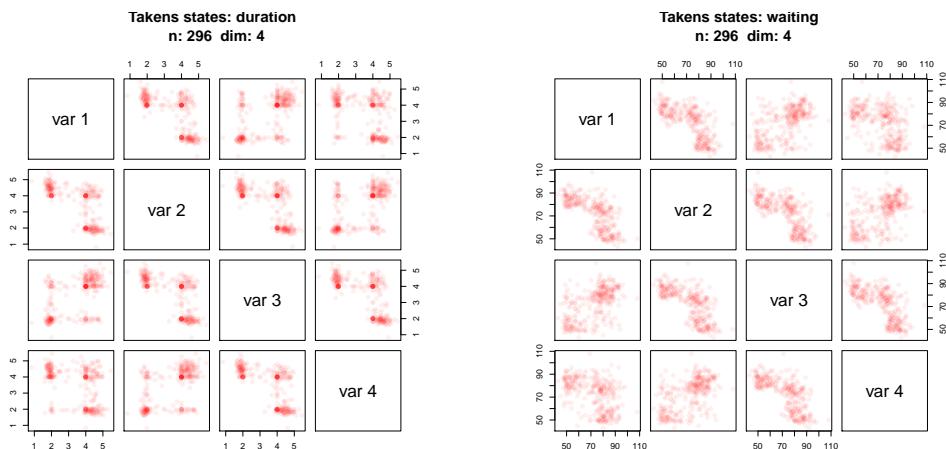


FIGURE 38. Old Faithful Geyser eruption durations and waiting time. Takens states, dim=4. Time used: 0.829 sec.

Input
`durationneighs4<- findAllNeighbours(takens.duration4, radius=2.4)`
`waitingneighs4<-findAllNeighbours(takens.waiting4, radius=20.0)`

Input

```
local.recurrencePlotAux(durationneighs4)
```

Input

```
local.recurrencePlotAux(waitingneighs4)
```

See Figure 39.

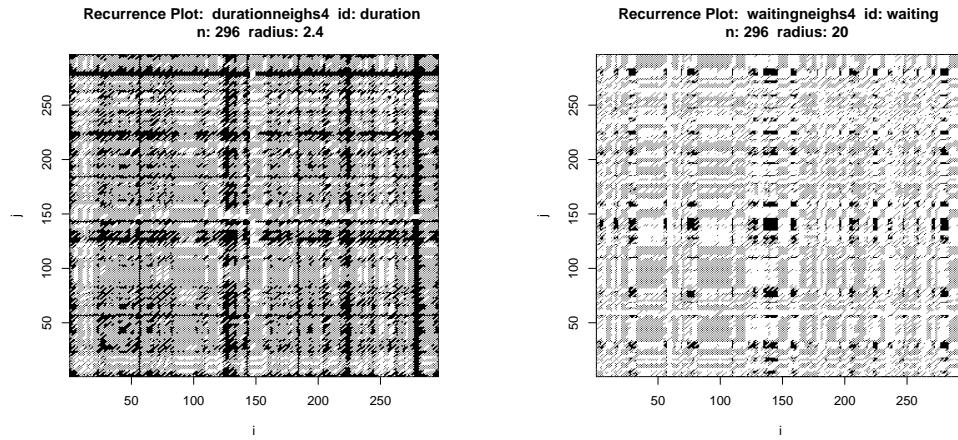


FIGURE 39. Old Faithful Geyser eruption durations and waiting time.
Time used: 1.099 sec.

Assuming that labels etc. are propagated as attributes, we can use a modified version of `recurrencePlot()`

Input

```
# univariate variant, assuming attributes
local.recurrencePlot1=function(neighs){
  dim <- attr(neighs, "embedding.dim")
  lag <- attr(neighs, "time.lag")
  radius <- attr(neighs, "radius")
  # just for reference. This function is inlined
  neighbourListNeighbourMatrix = function(){
    #neighs.matrix = Diagonal(ntakens)
    for (i in 1:ntakens){
      if (length(neighs[[i]])>0){
        for (j in neighs[[i]]){
          neighs.matrix[i,j] = 1
        }
      }
    }
    return (neighs.matrix)
  }

  ntakens=length(neighs)
  neighs.matrix <- matrix(nrow=ntakens,ncol=ntakens)
  #neighbourListNeighbourMatrix()
  #neighs.matrix = Diagonal(ntakens)
  for (i in 1:ntakens){
    neighs.matrix[i,i] = 1 # do we want the diagonal fixed to 1
    if (length(neighs[[i]])>0){
      for (j in neighs[[i]]){
```

```

        neigs.matrix[i,j] = 1
    }
}
}

main <- paste("Recurrence Plot: ",
              deparse(substitute(neigs)))
)
more <- NULL

#use compones of neights if available
if (!is.null(dim)) more <- paste(more, " dim:",dim)
if (!is.null(lag)) more <- paste(more, " lag:",lag)
if (!is.null(radius)) more <- paste(more, " radius:",radius)

if (!is.null(more)) main <- paste(main, "\n",more)

# need no print because it is not a trellis object!!
#print(
  image(x=1:ntakens, y=1:ntakens,
         z=neigs.matrix,xlab="i", ylab="j",
         col="black",
         #xlim=c(1,ntakens), ylim=c(1,ntakens),
         useRaster=TRUE, #? is this safe??
         main=main
         )
#
  )
}

}

```

Input

```

oldpar <- par(mfrow=c(1,2))
local.recurrencePlot1(durationneighs4)
local.recurrencePlot1(waitingneighs4)
par(oldpar)

```

Input

```

showrqa(takens.duration4, radius=3*0.8)

```

Output

```

duration n: 296 Dim: 4
Radius: 2.4 Recurrence coverage REC: 0.554 log(REC)/log(R): -0.675
Determinism: 0.986 Laminarity: 0.562
DIV: 0.011
Trend: 0 Entropy: 2.994
Diagonal lines max: 88 Mean: 9.147 Mean off main: 9.092
Vertical lines max: 147 Mean: 4.264

```

RQA Example case: Old Faithful Geyser eruption durations. Radius=2.4 Dim=4. Time used: 1.495 sec. For graphical ouput, see Figure 40 on the next page.

Each plot shows a symmetric matrix. Since dimensions match, we can use the upper and lower triangle to allow comparison of both series in one plot, comparing the upper and lower triangle.

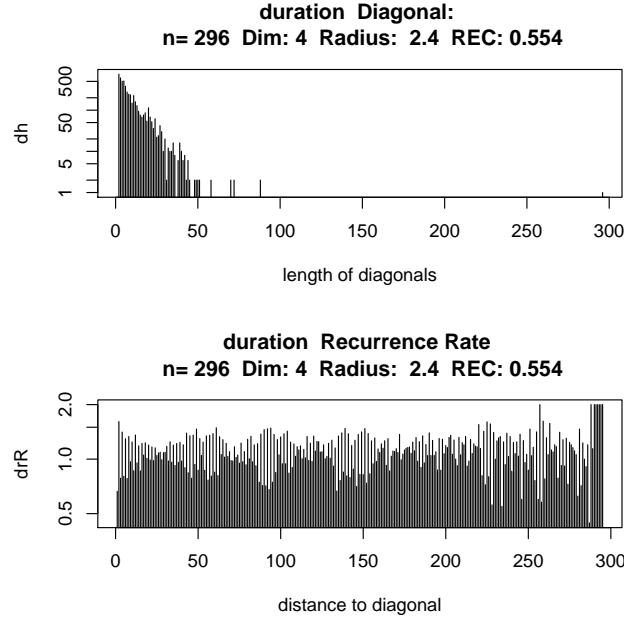


FIGURE 40. RQA. Example case: Old Faithful Geyser eruption durations. Radius=2.4 Dim=4, 0.64

Input

```

# bivariate variant, assuming attributes
# same dimension and size required
local.recurrencePlot2=function(neighs1, neighs2){
  dim1 <- attr(neighs1,"embedding.dim")
  lag1 <- attr(neighs1,"time.lag")
  radius1 <- attr(neighs1,"radius")

  dim2 <- attr(neighs2,"embedding.dim")
  lag2 <- attr(neighs2,"time.lag")
  radius2 <- attr(neighs2,"radius")

  # just for reference. This function is inlined
  neighbourListNeighbourMatrix = function(){
    #neighs.matrix = Diagonal(ntakens)
    for (i in 1:ntakens){
      if (length(neighs[[i]])>0){
        for (j in neighs[[i]]){
          neighs.matrix[i,j] = 1
        }
      }
    }
    return (neighs.matrix)
  }

#1
  ntakens1=length(neighs1)
  neighs1.matrix <- matrix(nrow=ntakens1,ncol=ntakens1)
  #neighbourListNeighbourMatrix()
  #neighs.matrix = Diagonal(ntakens)
  for (i in 1:ntakens1){
    neighs1.matrix[i,i] = 1 # do we want the diagonal fixed to 1
    if (length(neighs1[[i]])>0){

```

```

        for (j in neighs1[[i]]){
            neighs1.matrix[i,j] = 1
        }
    }
}

#2
ntakens2=length(neighs2)
neighs2.matrix <- matrix(nrow=ntakens2,ncol=ntakens2)
#neighbourListNeighbourMatrix()
#neighs.matrix = Diagonal(ntakens)
for (i in 1:ntakens2){
    neighs2.matrix[i,i] = 1 # do we want the diagonal fixed to 1
    if (length(neighs2[[i]])>0){
        for (j in neighs2[[i]]){
            neighs2.matrix[i,j] = 1
        }
    }
}
# merge
neighs.matrix <- neighs1.matrix
# replace upper triangle by neighs2.matrix
for (i in 1:ntakens2){
    for (j in i:ntakens2)
        neighs.matrix[i,j] <- -neighs2.matrix[i,j] #for colour
}

main <- paste("Recurrence Plot: ",
              deparse(substitute(neighs1)),
              deparse(substitute(neighs2))
              )
more <- NULL

#use compones of neights if available
if (!is.null(dim1)) more <- paste(more," dim:",dim1, dim2)
if (!is.null(lag1)) more <- paste(more," lag:",lag1, lag2)
if (!is.null(radius1)) more <- paste(more," radius:",radius1, radius2)

if (!is.null(more)) main <- paste(main,"\n",more)
#
ntakens <- ntakens1

# need no print because it is not a trellis object!!
#print(
#image(x=1:ntakens, y=1:ntakens,
#      z=neighs.matrix,xlab="i", ylab="j",
#      col=c("red","blue"),
#      xlim=c(1,ntakens), ylim=c(1,ntakens),
#      useRaster=TRUE, #? is this safe??
#      main=main
#      )
#      )
}

```

```
oldpar <- par(mfrow=c(1,1))
local.recurrencePlot2(durationneighs4,waitingneighs4)
par(oldpar)
```

See Figure 41.

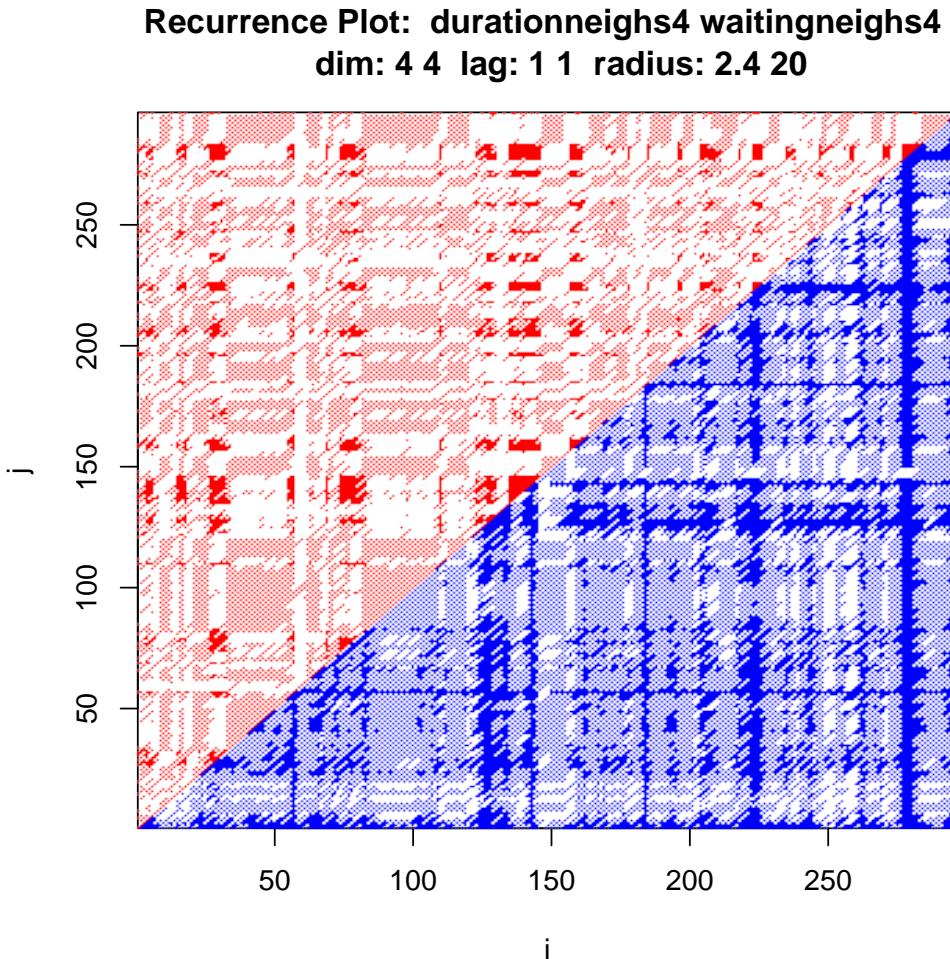


FIGURE 41. Recurrence plot: Lower triangle: duration. Upper triangle: waiting.

So far, the data have been handled as a pair of one-dimensional problems. Looking at the data as a bivariate problem requires to use a bivariate distance to define neighbours. See Marwan and Kurths [2002], Marwan *et al.* [2002].

Marwan uses a “covariance”

$$CR[i, j] = \Theta(\epsilon - |xv[i] - yv[j]|)$$

a maximumdistance as ||

Here is a brute force implementation

Signed distances may be used for experiments.

```
Input
maxdist <- function (x){ max(abs(x), na.rm=TRUE)} # works on delta
cordist <- function (x, y){ suppressWarnings(cor(x,y))}



---


Input
CRO <- function (xtakens, ytakens, sdist= maxdist) {
# using signed. Warnings for zero #
# variances are suppressed

  xl <- nrow(xtakens); yl <- nrow(ytakens)
  xname <- deparse(substitute(xtakens))
  yname <- deparse(substitute(ytakens))
  cr <- matrix(nrow=xl, ncol=yl)
  for (i in 1:xl)
    for (j in 1:yl)
    {
      cr[i,j] <- sdist(xtakens[i,]- ytakens[j,])
    }
  return(cr)
}
```

ToDo: Epsilon/radius and heaviside
not use here - may
be handled in image
rendering.

ToDo: propagate
names from takens

Variant *CR2* allows a distance that is not facored via $x - y$.

```
Input
CR2 <- function (xtakens, ytakens, cdist= cordist) {
  xl <- nrow(xtakens); yl <- nrow(ytakens)
  xname <- deparse(substitute(xtakens))
  yname <- deparse(substitute(ytakens))
  cr <- matrix(nrow=xl, ncol=yl)
  for (i in 1:xl)
    for (j in 1:yl)
    {
      cr[i,j] <- cdist(xtakens[i,], ytakens[j,])
    }
  return(cr)
}
```

```
Input
## for experiments only. do not copy large matrices
crossrecurrencePlotFromMatrix <- function(neighs.matrix,
                                             zlim= range(neighs.matrix, na.rm=TRUE),
                                             main="Cross Recurrence plot",
                                             xlab="x Takens vector's index",
                                             ylab="y Takens vector's index",...){
  # need a print because it is (possibly) a trellis object!!
  rec.plot = image(neighs.matrix,
                    zlim= zlim,
                    x = 1: ncol(neighs.matrix),
                    y = 1: nrow(neighs.matrix),
                    main = main, xlab = xlab, ylab = ylab,
                    ...)
  print(rec.plot)
  rec.plot
}
```

Raw data may give a poor impression. Adjust e.g. for scale and location.

Input

```
cr4 <- CR0(takens.duration4,takens.waiting4)
cr4C <- CR2(takens.duration4,takens.waiting4)
```

Input

```
image(cr4)
# neighs.matrix <- cr4;range(cr4) # 70.5500 107.1667
```

A max distance.

Input

```
crossrecurrencePlotFromMatrix(cr4,
  main="Cross Recurrence plot\nnmax",
  xlab="duration4 index", ylab="waiting4 index") # ugly heat matrix
```

Output

```
NULL
NULL
```

Input

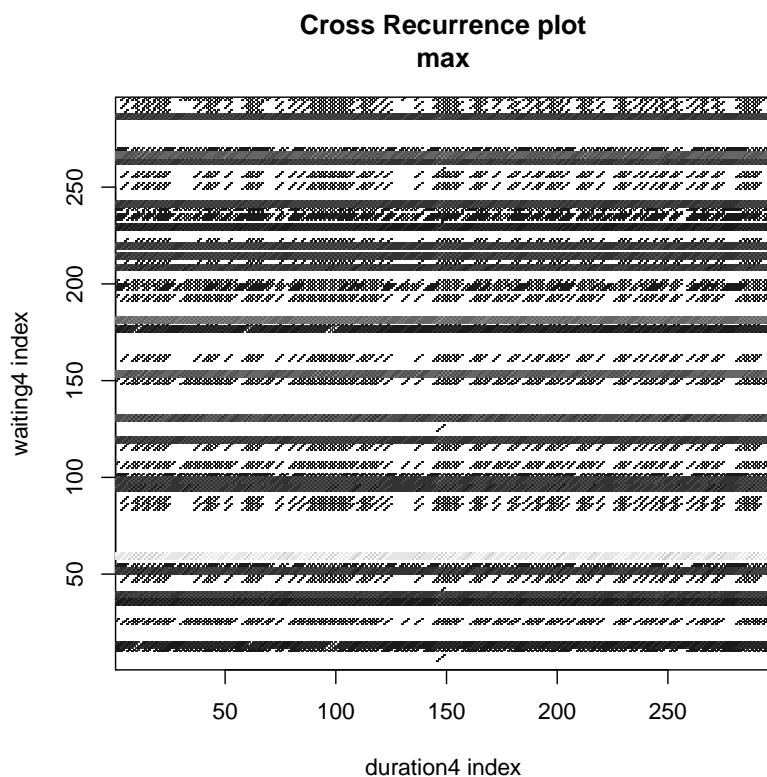
```
crossrecurrencePlotFromMatrix(cr4, zlim=c(85,108), col=grey((1:10)/10),
  main="Cross Recurrence plot\nnmax",
  xlab="duration4 index", ylab="waiting4 index")
```

Output

```
NULL
NULL
```

Input

```
# near conventional bw,
# introducing radius/cut by zlim
```

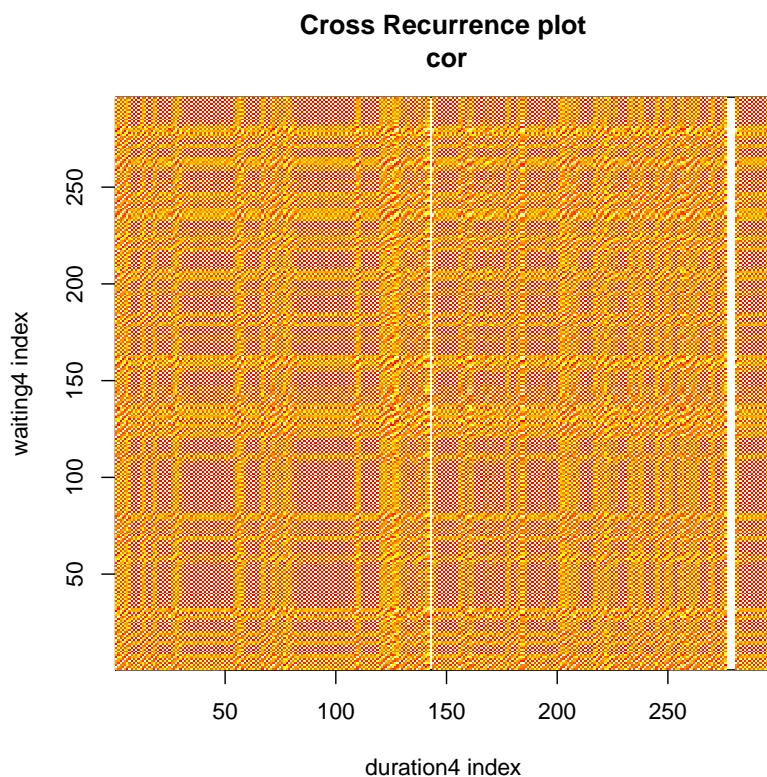


Input

```
# a correlation distance
crossrecurrencePlotFromMatrix(cr4C,
main="Cross Recurrence plot\n cor",
xlab="duration4 index", ylab="waiting4 index") # ugly heat matrix
```

Output

```
NULL
NULL
```



Input

```
quantile(cr4C, na.rm=TRUE)
```

Output

0%	25%	50%	75%	100%
-1.00000000	-0.68688423	-0.03466478	0.72172812	1.00000000

Input

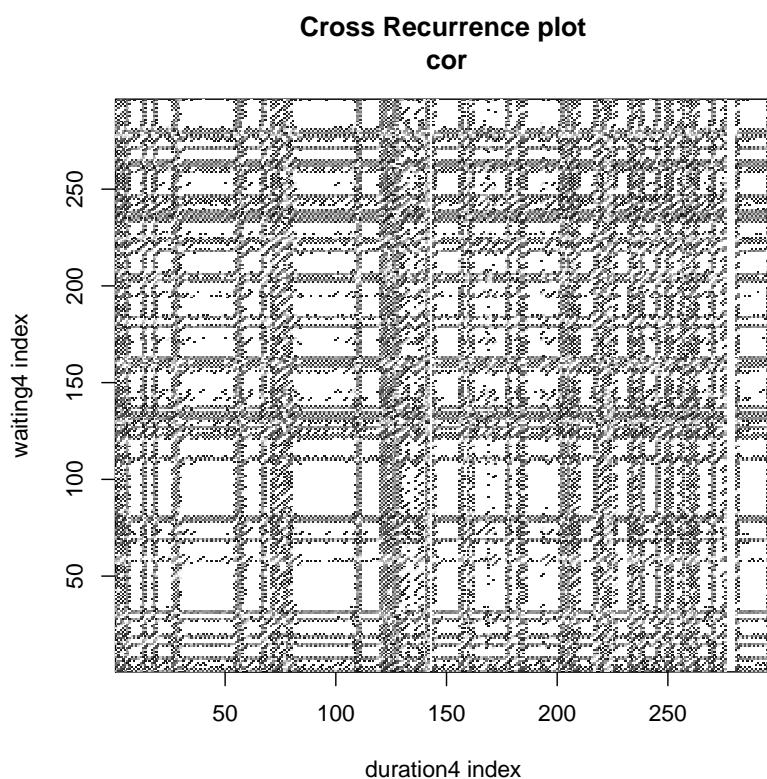
```
crossrecurrencePlotFromMatrix(cr4C, zlim=c(-0.7,0.7), col=grey((1:10)/10),
  main="Cross Recurrence plot\n cor",
  xlab="duration4 index", ylab="waiting4 index")
```

Output

```
NULL
NULL
```

Input

```
# near conventional
# introducing radius/cut by zlim
```



8. CASE STUDY: GEYSER DATA –DEFUNCT

Defunct. hopefully completely replaced by bivariate analysis in previous chapter.

8.1. Geyser Eruption Durations. See Figure 42.

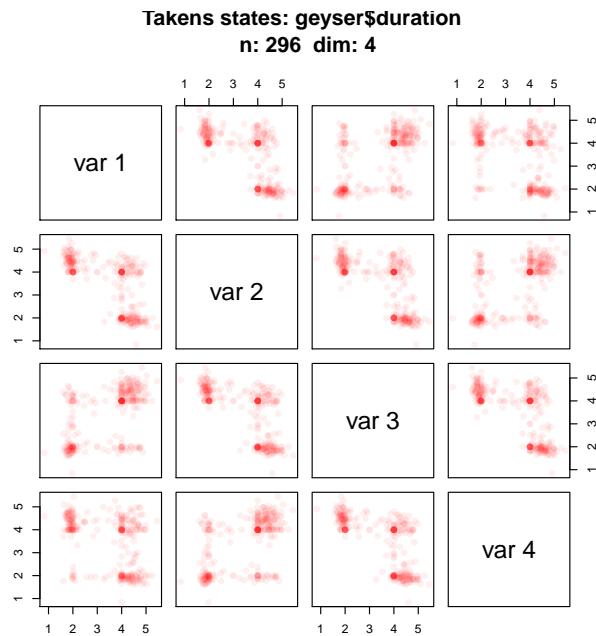


FIGURE 42. Recurrence plot. Old Faithful Geyser eruption durations.
Time used: 0.001 sec.

ToDo: remove this section

8.1.1. Geyser eruption durations. Dim=2.

Input

```
eruptionstakens2 <-
  local.buildTakens(time.series=geyser$duration,
                    embedding.dim=2, time.lag=1)
statepairs(eruptionstakens2) #dim=2
```

See Figure 43 on the facing page.

Input

```
statepairs(eruptionstakens2, nooverlap=TRUE) #dim=2
```

See Figure 44 on the next page

Input

```
eruptionsneighs2 <- local.findAllNeighbours(eruptionstakens2,
                                                radius=0.8)
save(eruptionsneighs2, file="eruptionsneighs2.RData")
# load(file="eruptionsneighs2.RData")
local.recurrencePlotAux(eruptionsneighs2)
```

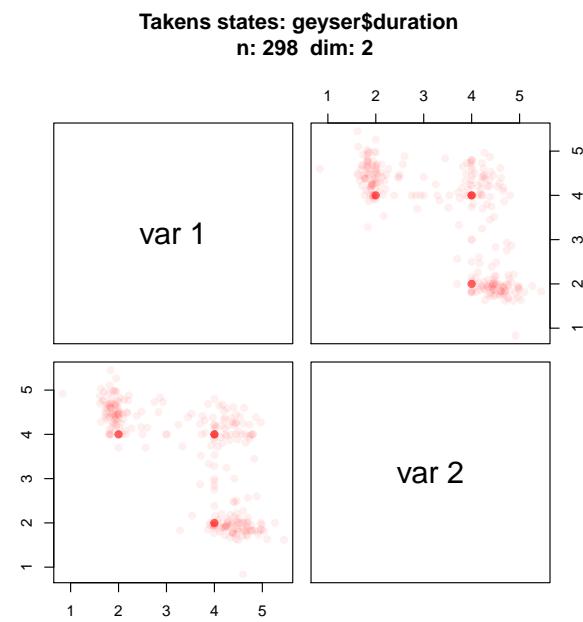


FIGURE 43. Recurrence plot. Old Faithful Geyser eruption durations.
Dim=2. Time used: 0.068 sec.

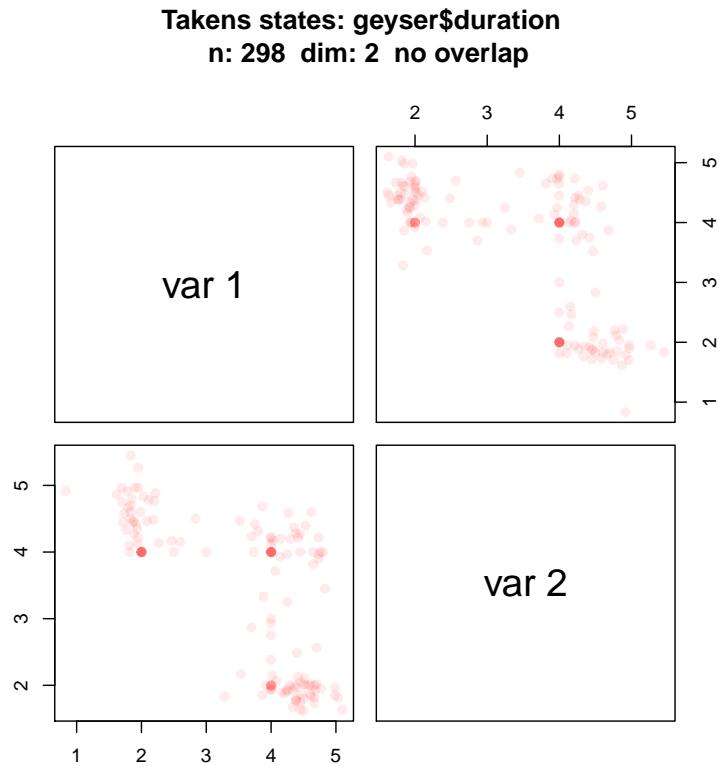


FIGURE 44. Example case: Old Faithful Geyser eruption durations.
Dim=2. Time used: 0.117 sec.

See Figure 45.

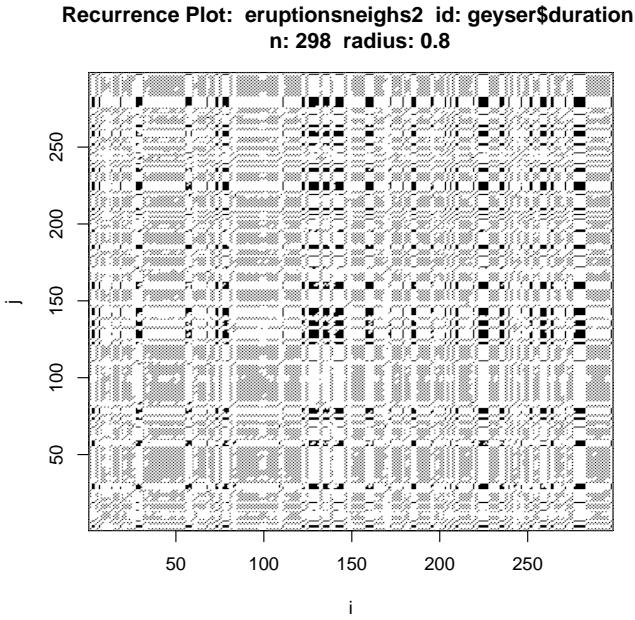


FIGURE 45. Recurrence plot. Old Faithful Geyser eruption durations.
Dim=2. Time used: 0.126 sec.

Input	
<code>showrqa(eruptionstakens2, radius=0.8)</code>	
Output	
<code>geyser\$duration n: 298 Dim: 2</code>	
<code>Radius: 0.8 Recurrence coverage REC: 0.274 log(REC)/log(R): 5.806</code>	
<code>Determinism: 0.892 Laminarity: 0.205</code>	
<code>DIV: 0.045</code>	
<code>Trend: 0 Entropy: 1.691</code>	
<code>Diagonal lines max: 22 Mean: 3.644 Mean off main: 3.595</code>	
<code>Vertical lines max: 7 Mean: 3.457</code>	

RQA Example case: Old Faithful Geyser eruption durations. Dim=2. Time used: 0.189 sec. For graphical output, see Figure 46 on the next page.

8.1.2. Geyser eruptions. Dim=4.

Input	
<code>eruptionsneighs4 <- local.findAllNeighbours(takens.duration4, radius=0.8)</code>	
<code>save(eruptionsneighs4, file="eruptionsneighs4.RData")</code>	
Input	
<code>load(file="eruptionsneighs4.RData")</code>	
<code>local.recurrencePlotAux(eruptionsneighs4)</code>	

See Figure 47 on the facing page.

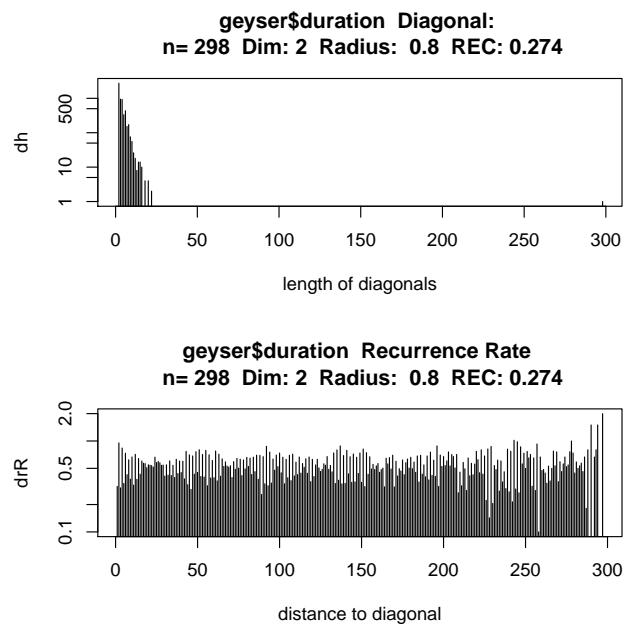


FIGURE 46. RQA. Example case: Old Faithful Geyser eruption durations. Dim=2, 0.64

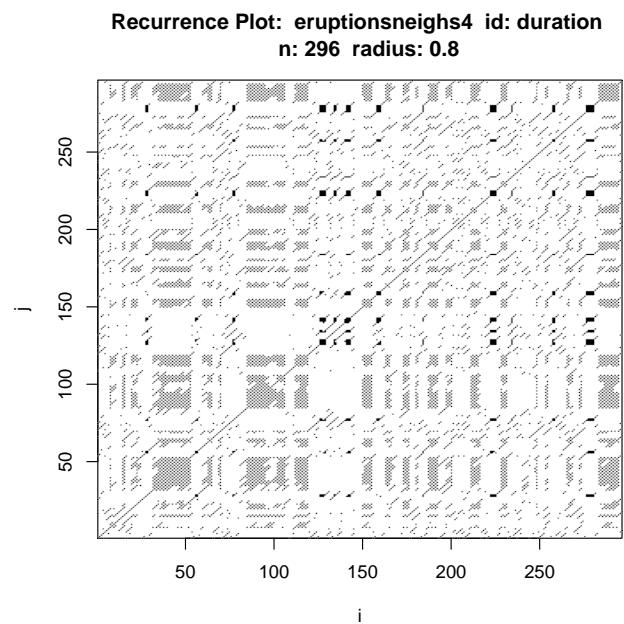


FIGURE 47. Recurrence plot. Example case: Old Faithful Geyser eruption durations. Dim=4. Time used: 0.101 sec.

Input

```
showrqa(takens.duration4, radius=0.8)
```

Output

```

duration n: 296 Dim: 4
Radius: 0.8 Recurrence coverage REC: 0.112 log(REC)/log(R): 9.822
Determinism: 0.903 Laminarity: 0.076
DIV: 0.05
Trend: 0 Entropy: 1.779
Diagonal lines max: 20 Mean: 3.919 Mean off main: 3.79
Vertical lines max: 5 Mean: 3.041

```

See Figure 48.

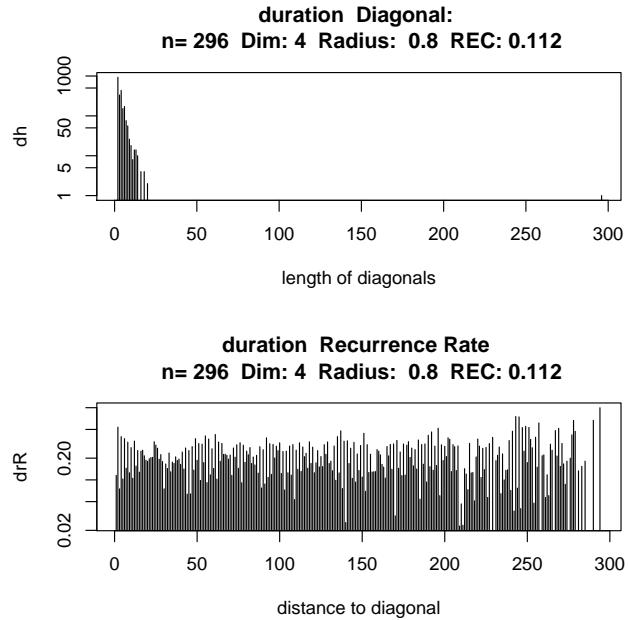


FIGURE 48. Recurrence plot. Old Faithful Geyser eruption durations.
Dim=4. Time used: 0.157 sec.

8.1.3. Geyser eruption durations. Dim=8.

```

eruptionstakens8 <- local.buildTakens( time.series=geyser$duration,
                                         embedding.dim=8,time.lag=1)
statepairs(eruptionstakens8) #dim=8

```

See Figure 49 on the facing page.

```

statepairs(eruptionstakens8, nooverlap=TRUE) #dim=8

```

See Figure 50 on page 74.

```

eruptionsneighs8 <- local.findAllNeighbours(eruptionstakens8,
                                                radius=2.6)
save(eruptionsneighs8, file="eruptionsneighs8.RData")
#load(file="eruptionsneighs8.RData")
local.recurrencePlotAux(eruptionsneighs8)

```

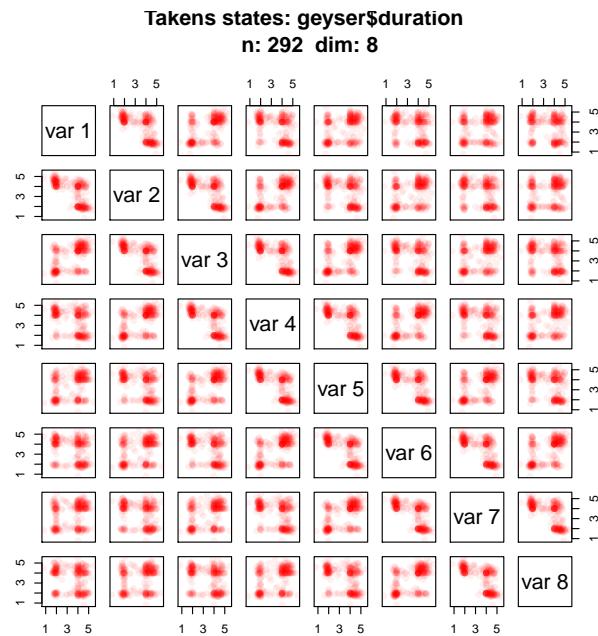


FIGURE 49. Recurrence plot. Old Faithful Geyser eruption durations.
Dim=8. Time used: 0.89 sec.

See Figure 51 on page 75.

Input

```
showrqa(eruptionstakens8, radius=2.6)
```

Output

```
geyser$duration n: 292 Dim: 8
Radius: 2.6 Recurrence coverage REC: 0.494 log(REC)/log(R): -0.738
Determinism: 0.991 Laminarity: 0.5
DIV: 0.011
Trend: 0 Entropy: 3.338
Diagonal lines max: 93 Mean: 12.635 Mean off main: 12.55
Vertical lines max: 36 Mean: 4.073
```

RQA Example case: Old Faithful Geyser eruption durations. Dim=8. Time used: 0.334 sec. For graphical output, see Figure 52 on page 75.

Takens states: geyser\$duration
n: 292 dim: 8 no overlap

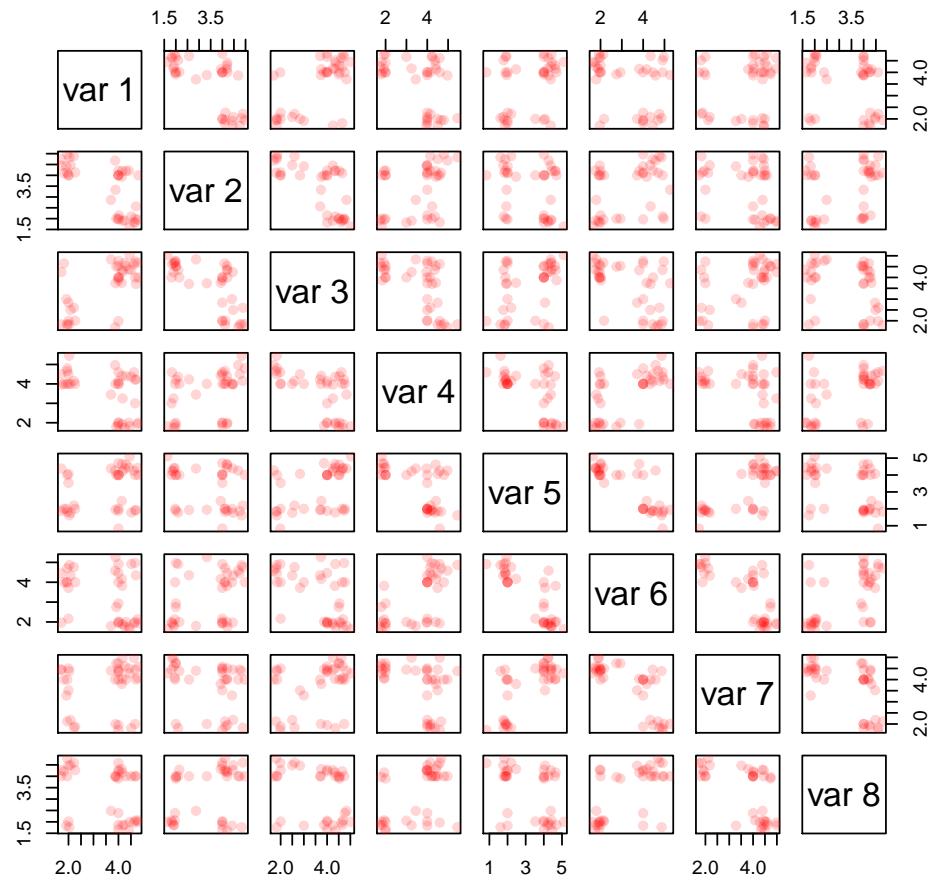


FIGURE 50. Example case: Old Faithful Geyser eruption durations.
Dim=8. Time used: 1.116 sec.

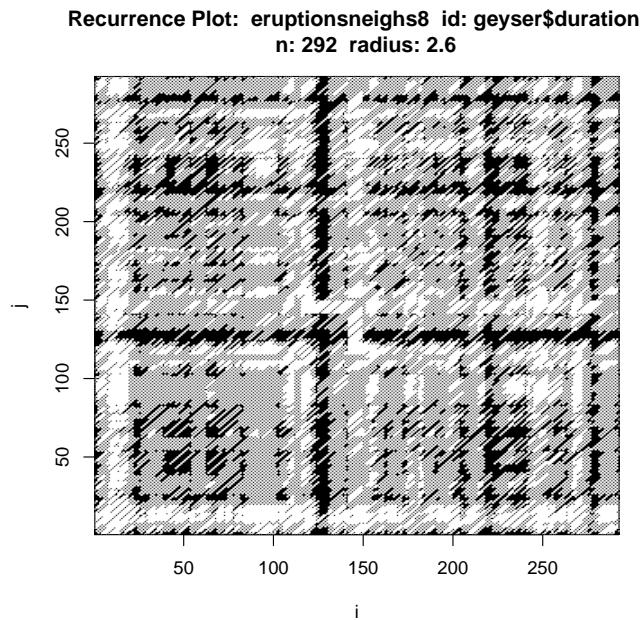


FIGURE 51. Recurrence plot. Example case: Old Faithful Geyser eruption durations. Dim=8. Time used: 0.234 sec.

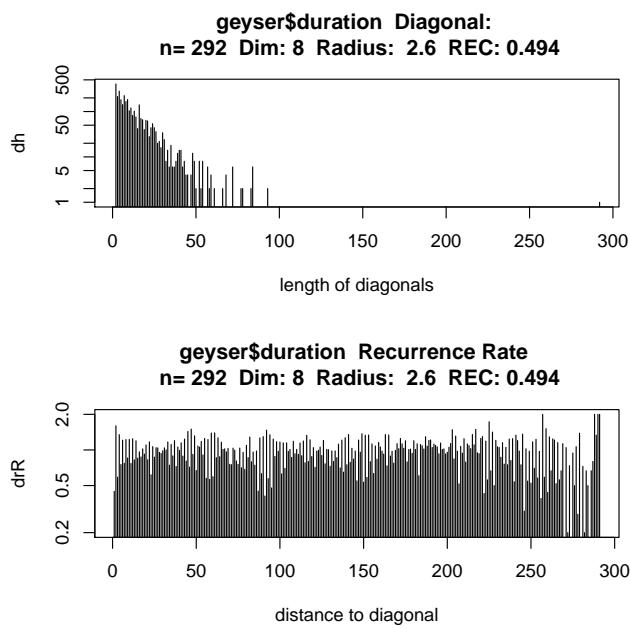


FIGURE 52. RQA. Example case: Old Faithful Geyser eruption durations. Dim=8, 0.64

8.1.4. *Geyser eruption durations: Comparison by Dimension.* For comparison, recurrence plots for the Geyser data with varying dimension are in Figure 53

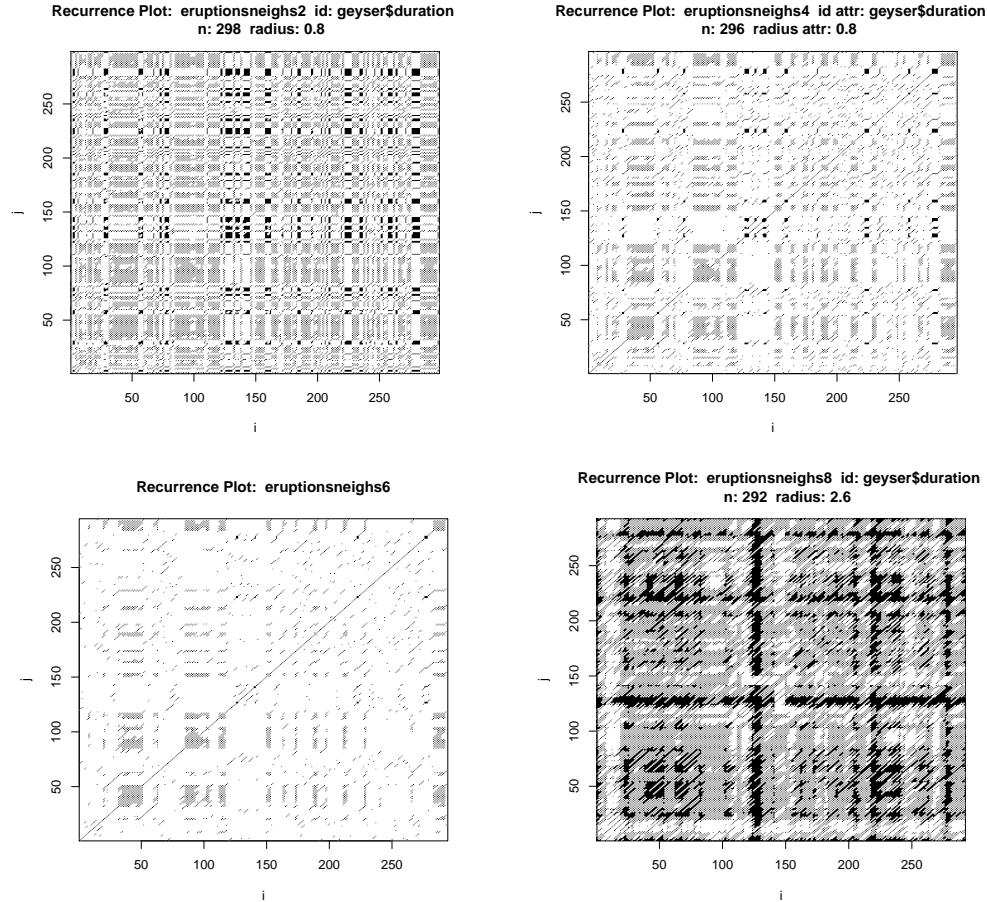


FIGURE 53. Recurrence Plot. Example case: Old Faithful Geyser eruptions. Dim=2, 4, 6, 8.

8.2. **Geyser Waiting, lag=4.** Note: is this of any use? Any good example for use of lag?

Input

```
waitingtakens <-
  local.buildTakens( time.series=geyser$waiting,
                     embedding.dim=4, time.lag=4)
statepairs(waitingtakens) #dim=4
```

See Figure 54 on the next page.

Input

```
waitingneighs <- local.findAllNeighbours(waitingtakens, radius=16)
save(waitingneighs, file="waitingneighs.Rdata")
```

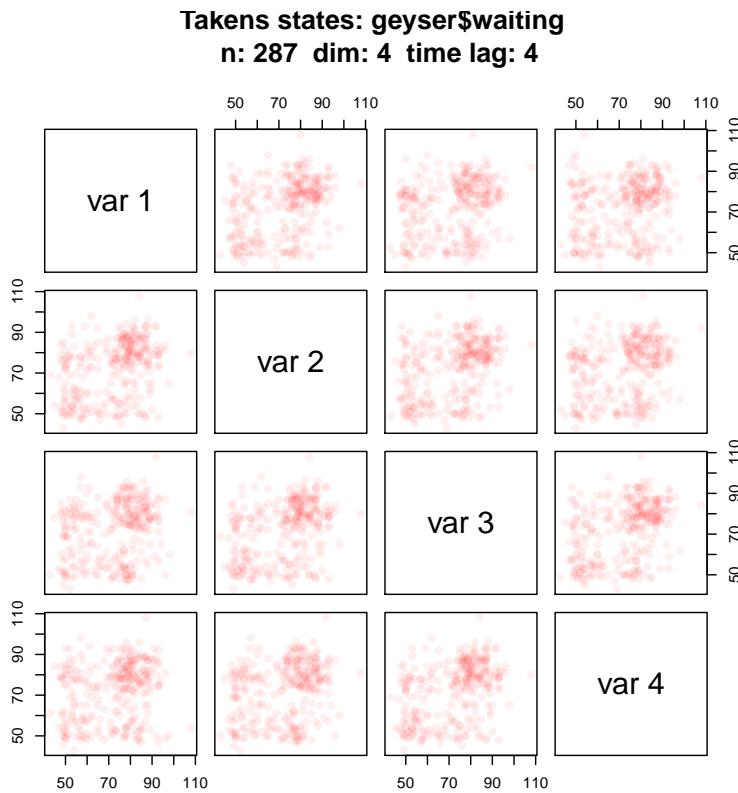


FIGURE 54. Example case: Old Faithful Geyser waiting. lag 4. Time used: 0.574 sec.

Input

```
showrqa(waitingtakens, radius=16)
```

Output

```
geyser$waiting n: 287 Dim: 4
Radius: 16 Recurrence coverage REC: 0.137 log(REC)/log(R): -0.718
Determinism: 0.382 Laminarity: 0.053
DIV: 0.053
Trend: 0 Entropy: 1.002
Diagonal lines max: 19 Mean: 2.878 Mean off main: 2.688
Vertical lines max: 3 Mean: 2.315
```

RQA Example case: Old Faithful Geyser waiting. Time used: 0.069 sec. For graphical output, see Figure 55 on the following page.

Input

```
load(file="waitingneighs.RData")
local.recurrencePlotAux(waitingneighs)
```

See Figure 56 on the next page.

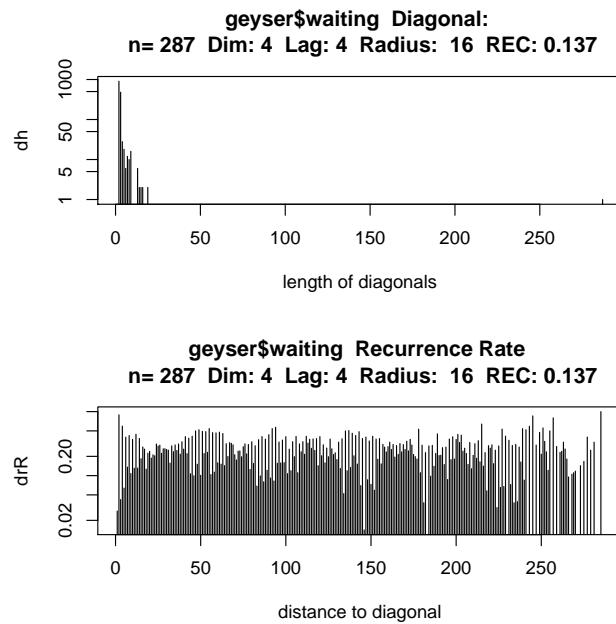


FIGURE 55. RQA. Example case: Old Faithful Geyser waiting, 0.64

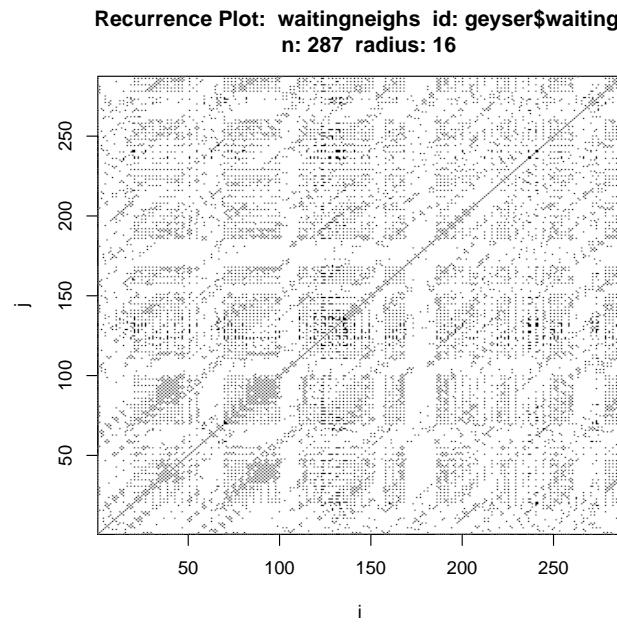


FIGURE 56. Recurrence plot. Example case: Old Faithful Geyser waiting. Time used: 0.171 sec.

9. CASE STUDY: HRV DATA EXAMPLE.BEATS

Note for data analysis: The data include missing beats, or spurious artefacts. These need to be handled. Graphical display is heavily affected by the scales implied by outliers.

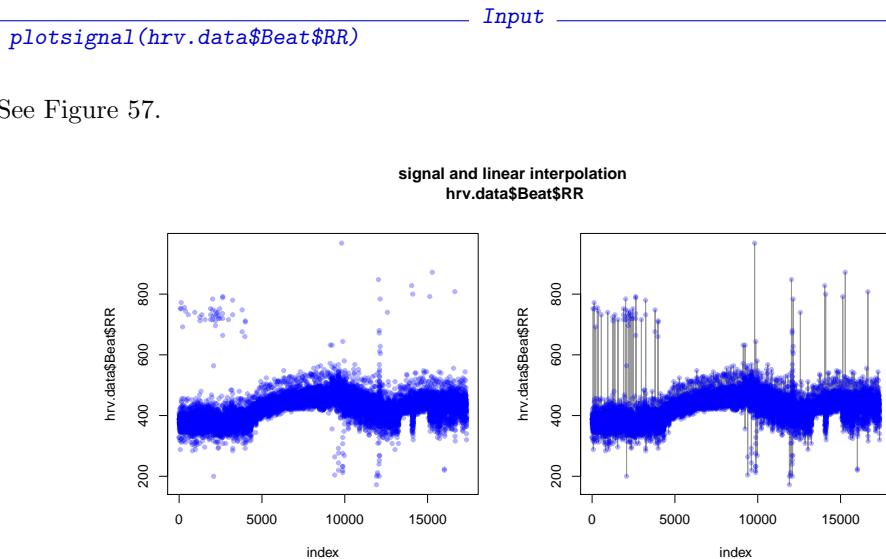
Only 1024 data points used in recurrence plots in this section

Input

```
#stop("Stopping before RHRV")

#install.packages("RHRV",repos="http://r-forge.r-project.org",type="source")
if (!require("RHRV")) {
  install.packages("RHRV")
  library(RHRV)
}
load("/users/gs/projects/rforge/rhrv/pkg/data/HRVData.rda")
load("/users/gs/projects/rforge/rhrv/pkg/data/HRVProcessedData.rda")
#####
### code chunk number 1: creation
#####
hrv.data = CreateHRVData()
hrv.data = SetVerbose(hrv.data, TRUE )
#####
### code chunk number 3: loading
#####
hrv.data = LoadBeatAscii(hrv.data, "example.beats",
  RecordPath = "/users/gs/projects/rforge/rhrv/tutorial/beatsFolder")
#      RecordPath = "beatsFolder"

#####
### code chunk number 4: derivating
#####
hrv.data = BuildNIHR(hrv.data)
```



See Figure 57.

To Do: We have outliers at approximately $2 \times \text{RR}$. Could this be an artefact of preprocessing, filtering out too many impulses?

FIGURE 57. RHRV tutorial example.beats. Signal and linear interpolation.

```
Input
hrvRRtakens4 <- local.buildTakens( time.series=hrv.data$Beat$RR[1:nsignal],
                                     embedding.dim=4, time.lag=1)
statepairs(hrvRRtakens4) #dim=4
```

See Figure 58.

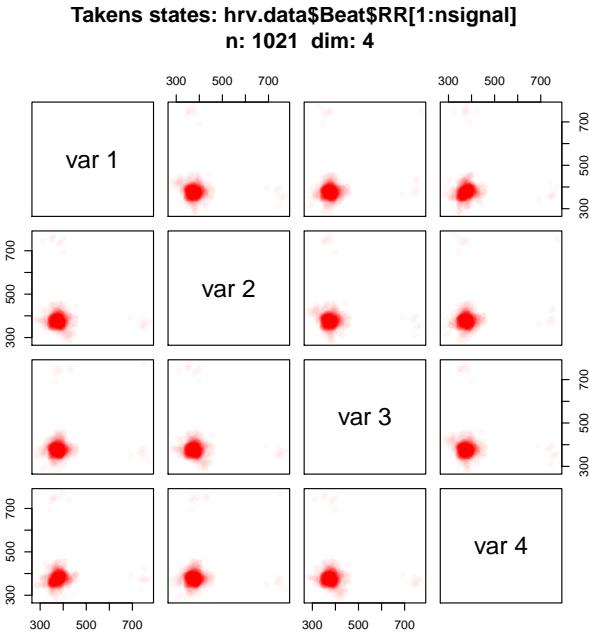


FIGURE 58. Recurrence plot. RHRV tutorial example.beats.. Time used: 0.53 sec.

```
Input
statepairs(hrvRRtakens4, rank=TRUE) #dim=4
```

See Figure 59 on the facing page.

```
Input
statecoplet(hrvRRtakens4) #dim=4
```

See Figure 60 on page 82.

```
Input
hrvRRtakens4 <- local.buildTakens( time.series=hrv.data$Beat$RR[1:nsignal],
                                      embedding.dim=4, time.lag=1)
statepairs(hrvRRtakens4)
```

See Figure 61 on page 82.

```
Input
hrvRRneighs4 <- local.findAllNeighbours(hrvRRtakens4, radius=16)
save(hrvRRneighs4, file="hrvRRneighs4.Rdata")
```

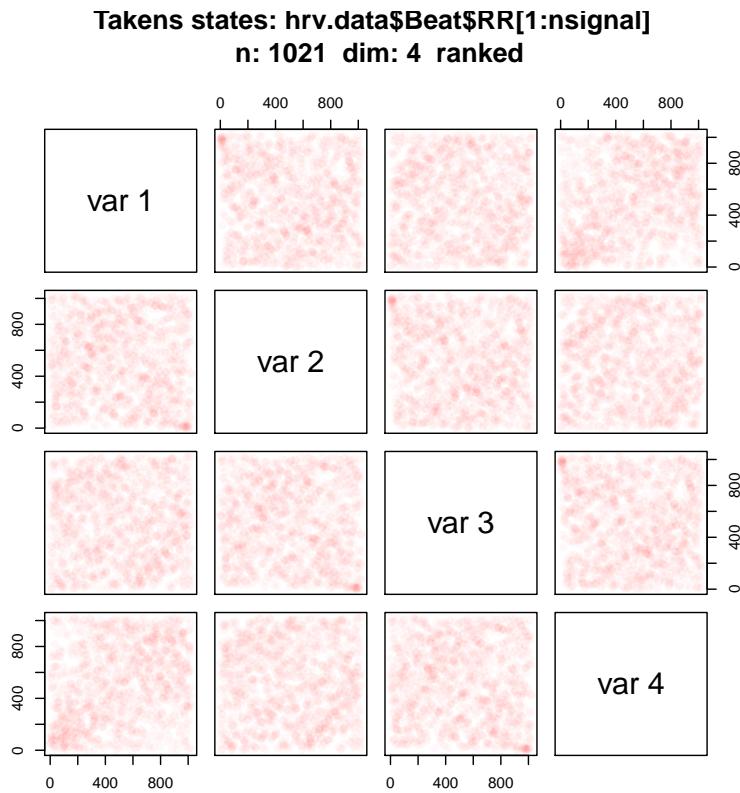


FIGURE 59. RHRV tutorial example.beats. Ranked data. Time used:
1.161 sec.

Time used: 0.701 sec.

Input

```
load(file="hrvRRneighs4.RData")
local.recurrencePlotAux(hrvRRneighs4)
```

See Figure 62 on page 83.

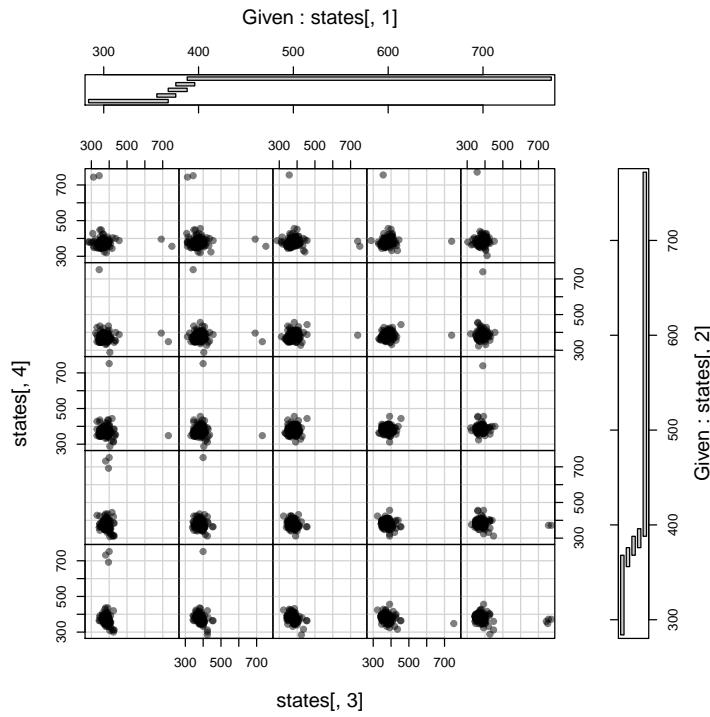


FIGURE 60. State coplot. RHRV tutorial example.beats. Time used: 0.208 sec.

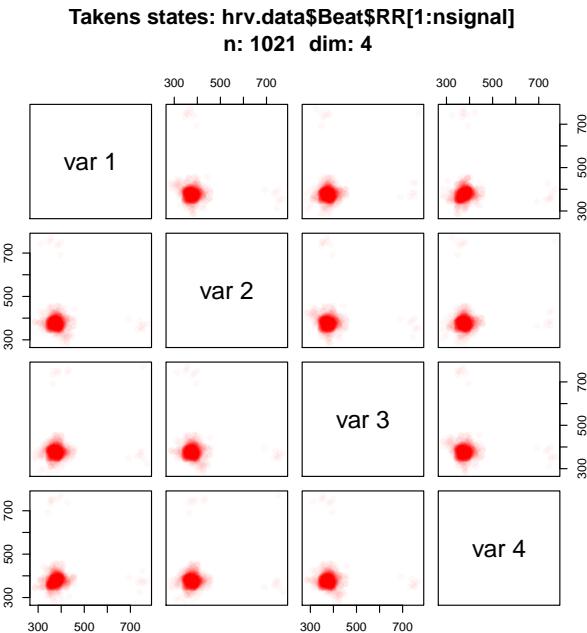


FIGURE 61. Recurrence plot. RHRV tutorial example.beats. Time used: 0.633 sec.

Recurrence Plot: hrvRRneighs4 id: hrv.data\$Beat\$RR[1:nsign:
n: 1021 radius: 16

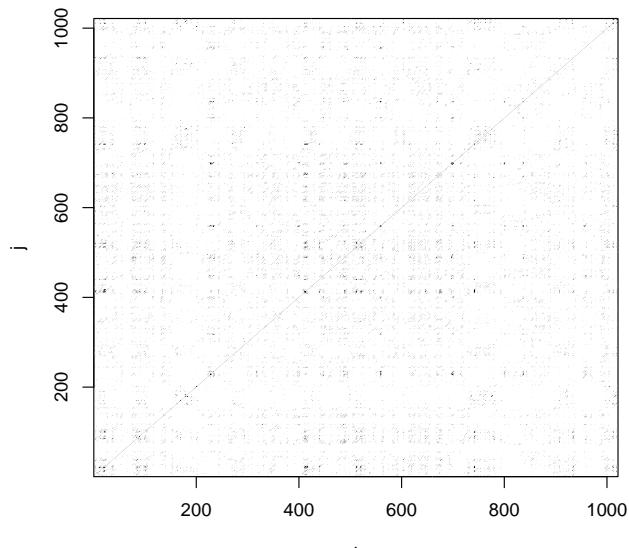


FIGURE 62. Recurrence plot. Example: RHRV tutorial example.beats.
Dim=4.. Time used: 0.679 sec.

We should expect the breathing rhythm, so a time lag in the order of 10 is to be expected.

9.0.1. RHRV: *example.beats* - Comparison by Dimension.

Input

```
hrvRRtakens2 <- local.buildTakens( time.series=hrv.data$Beat$RR[1:nsignal],
  embedding.dim=2,time.lag=1)
hrvRRneighs2 <- local.findAllNeighbours(hrvRRtakens2, radius=16)
save(hrvRRneighs2, file="hrvRRneighs2.Rdata")
# load(file="hrvRRneighs2.RData")
local.recurrencePlotAux(hrvRRneighs2)
showrqa(hrvRRtakens2, do.hist=FALSE, radius=16)
```

Output

```
hrv.data$Beat$RR[1:nsignal] n: 1023 Dim: 2
Radius: 16 Recurrence coverage REC: 0.165 log(REC)/log(R): -0.65
Determinism: 0.651 Laminarity: 0.376
DIV: 0.056
Trend: 0 Entropy: 1.248
Diagonal lines max: 18 Mean: 2.841 Mean off main: 2.816
Vertical lines max: 14 Mean: 2.463
```

See Figure 63.

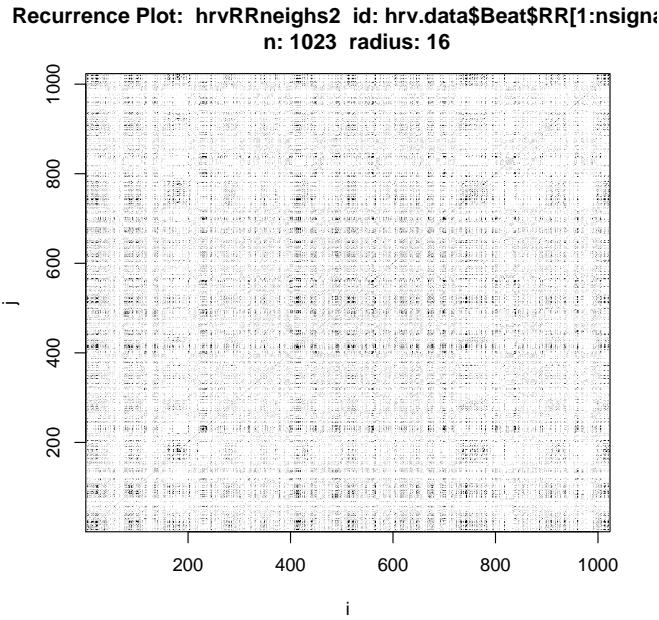


FIGURE 63. Recurrence plot. Dim=2.. Time used: 1.287 sec.

Input

```
hrvRRtakens6 <- local.buildTakens( time.series=hrv.data$Beat$RR[1:nsignal],
  embedding.dim=6,time.lag=1)
hrvRRneighs6 <- local.findAllNeighbours(hrvRRtakens6, radius=16)
save(hrvRRneighs6, file="hrvRRneighs6.Rdata")
# load(file="hrvRRneighs6.RData")
local.recurrencePlotAux(hrvRRneighs6)
```

Dim=6. Time used: 0.797 sec.

```
Input
hrvRRtakens8 <- local.buildTakens( time.series=hrv.data$Beat$RR[1:nSignal],
                                     embedding.dim=8, time.lag=1)
hrvRRneighs8 <- local.findAllNeighbours(hrvRRtakens8, radius=32)
save(hrvRRneighs8, file="hrvRRneighs8.Rdata")
# load(file="hrvRRneighs8.RData")
local.recurrencePlotAux(hrvRRneighs8)
```

Dim=8. Time used: 0.895 sec.

```
Input
hrvRRtakens12 <- local.buildTakens( time.series=hrv.data$Beat$RR[1:nSignal],
                                       embedding.dim=2, time.lag=1)
hrvRRneighs12 <- local.findAllNeighbours(hrvRRtakens12, radius=16)
save(hrvRRneighs12, file="hrvRRneighs12.Rdata")
# load(file="hrvRRneighs12.RData")
local.recurrencePlotAux(hrvRRneighs12)
```

Dim=12. Time used: 1.998 sec.

```
Input
hrvRRtakens16 <- local.buildTakens(
  time.series=hrv.data$Beat$RR[1:nSignal],
  embedding.dim=16, time.lag=1)
hrvRRneighs16 <- local.findAllNeighbours(hrvRRtakens16, radius=32)
save(hrvRRneighs16, file="hrvRRneighs16.Rdata")
# load(file="hrvRRneighs16.RData")
local.recurrencePlotAux(hrvRRneighs16)
```

Dim=16. Time used: 0.881 sec.

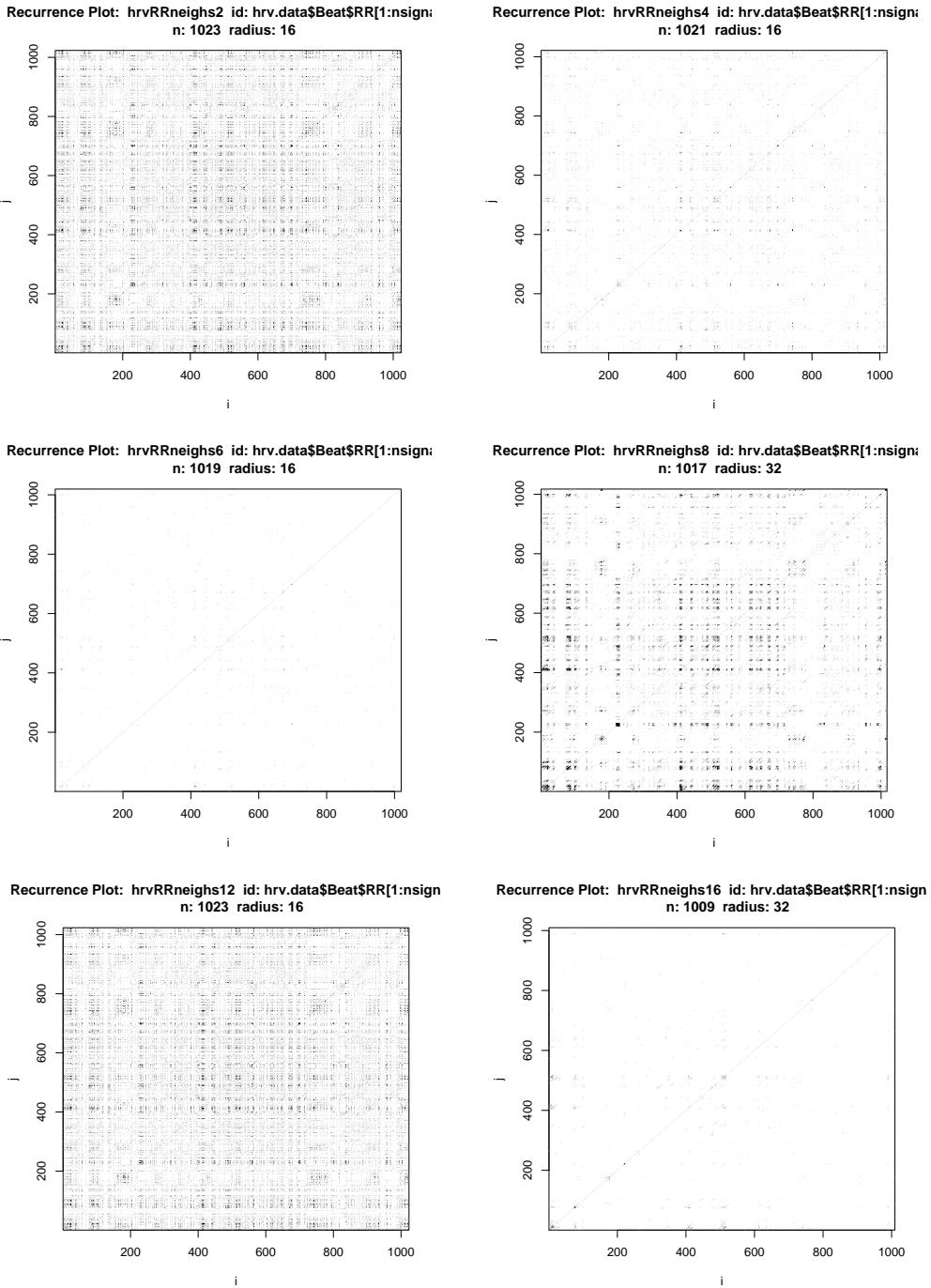


FIGURE 64. Recurrence Plot. Example case: RHRV tutorial example.beats. Dim=2, 4, 6, 8, 12, 16. Time used: 0.881 sec.

9.1. RHRV: example.beats - Hart Rate Variation. Since we are not interested in heart rate (or pulse), but in heart rate variation, a proposal is to use scaled differences.

ToDo: This is an experimental proposal

```

# source('/users/gs/projects/rforge/rhrv/pkg/R/BuildNIHR2.R', chdir = TRUE)
BuildNIDHR <-
function(HRVData, verbose=NULL) {
#-----
# Obtains instantaneous heart rate variation from beats positions
# D for difference. The scaled difference is recorded as variation HRRV
#-----
if (!is.null(verbose)) {
    cat(" --- Warning: deprecated argument, using SetVerbose() instead ---\n",
        " --- See help for more information!! ---\n")
    SetVerbose(HRVData,verbose)
}

if (HRVData$Verbose) {
    cat("** Calculating non-interpolated heart rate differences **\n")
}

if (is.null(HRVData$Beat$Time)) {
    cat(" --- ERROR: Beats positions not present...",
        " Impossible to calculate Heart Rate!! ---\n")
    return(HRVData)
}

NBeats=length(HRVData$Beat$Time)
if (HRVData$Verbose) {
    cat(" Number of beats:",NBeats,"\\n");
}

# addition gs
#using NA, not constant extrapolation as else in RHRV
#drr=c(NA,NA,1000.0* diff(HRVData$Beat$Time, lag=1 , differences=2))
HRVData$Beat$dRR=c(NA, NA,
    1000.0*diff(HRVData$Beat$Time, lag=1, differences=2))

HRVData$Beat$avRR=(c(NA,HRVData$Beat$RR[-1])+HRVData$Beat$RR)/2

HRVData$Beat$HRRV <- HRVData$Beat$dRR/HRVData$Beat$avRR
# end addition gs
return(HRVData)
}

```

differences for HRV

Input

```
hrv.data <- BuildNIDHR(hrv.data)
```

Output

```
** Calculating non-interpolated heart rate differences **
Number of beats: 17360
```

Input

```
HRRV <- hrv.data$Beat$HRRV
```

These are the displays of the Takens state space we used before, now for HRRV:

Input

```
plotsignal(HRRV)
```

See Figure 65,

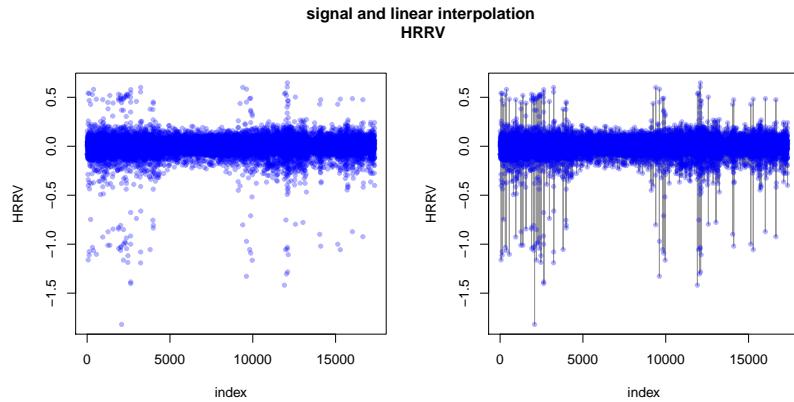


FIGURE 65. RHRV tutorial example.beats. HRRV Signal and linear interpolation.

Only 1024 data points used in this section

Input

```
hrvRRVtakens4 <-
  local.buildTakens( time.series=HRRV[1:nseries],
                     embedding.dim=4, time.lag=1)
statepairs(hrvRRVtakens4) #dim=4
```

See Figure 66 on the facing page

Input

```
statepairs(hrvRRVtakens4, rank=TRUE) #dim=4
```

ToDo: findAll-
Neighbours does not
handle NAs

Input

```
#use hack: findAllNeighbours does not handle NAs
hrvRRVneighs4 <- local.findAllNeighbours(hrvRRVtakens4[-(1:2),], radius=0.125)
save(hrvRRVneighs4, file="hrvRRVneighs4.Rdata")
```

Time used: 0.182 sec.

Input

```
load(file="hrvRRVneighs4.RData")
local.recurrencePlotAux(hrvRRVneighs4, dim=4, radius=0.125)
```

ToDo: check. There
seem to be strange
artefacts.

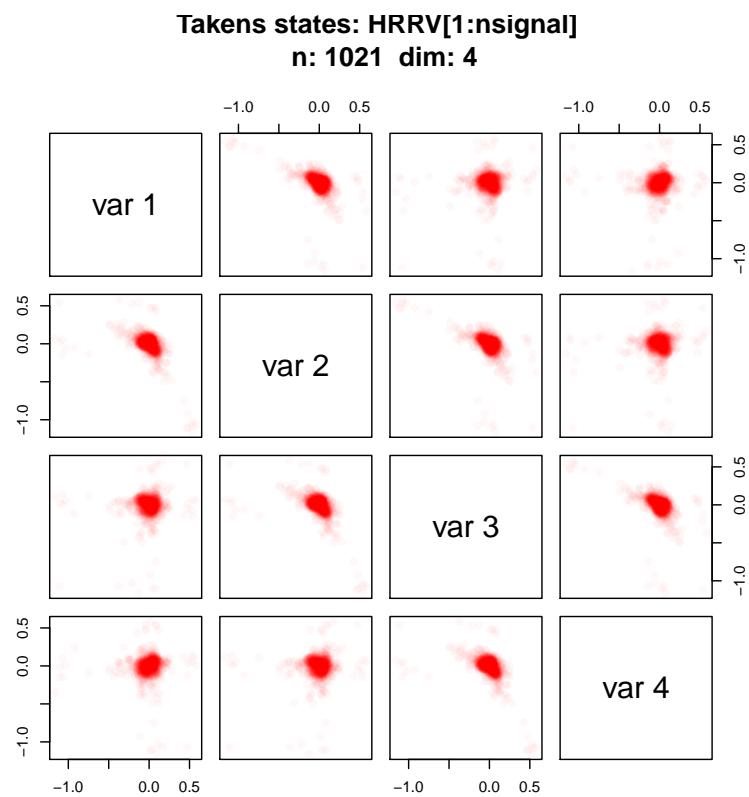


FIGURE 66. RHRV tutorial example.beats. HRRV Time used: 0.704 sec.

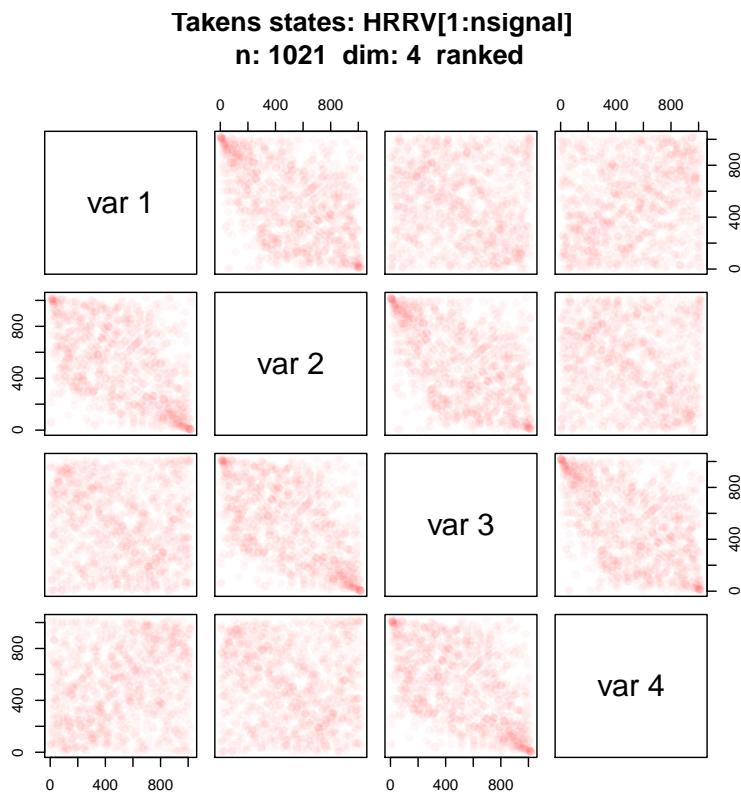


FIGURE 67. RHRV tutorial example.beats. Ranked HRRV data. Time used: 1.37 sec.

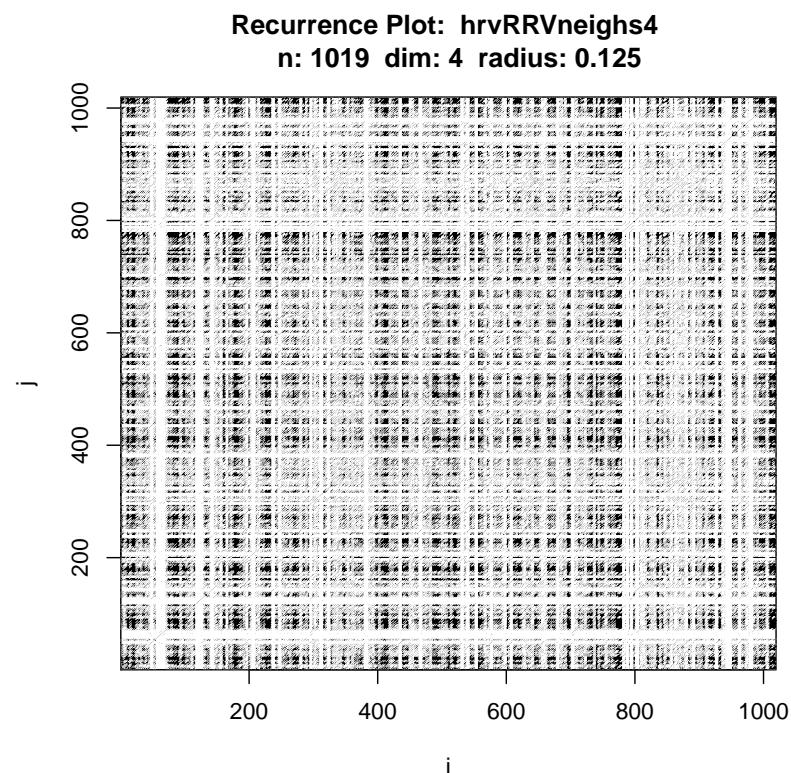


FIGURE 68. Recurrence Plot. Example case: RHRV tutorial example.beats. HRRV Dim=4. Time used: 1.388 sec.

We should expect the breathing rhythm, so a time lag in the order of 10 is to be expected.
ToDo: fix default setting for radius. Eckmann uses nearest neighbours with NN=10

9.1.1. RHRV: example.beats - RR Variation: Comparison by Dimension.

Input

```
hrvRRVtakens2 <- local.buildTakens( time.series=HRRV[1:nSignal],
      embedding.dim=2, time.lag=1)
hrvRRVneighs2 <- local.findAllNeighbours(hrvRRVtakens2[-(1:2),],
      radius=0.125)
save(hrvRRVneighs2, file="hrvRRVneighs2.Rdata")
# load(file="hrvRRVneighs2.RData")
local.recurrencePlotAux(hrvRRVneighs2, dim=2, radius=0.125)
showrqa(hrvRRVtakens2[-(1:2),], radius=0.125, do.hist=FALSE)
```

Output

```
hrvRRVtakens2[-(1:2), ] n: 1021 Dim: 2
Radius: 0.125 Recurrence coverage REC: 0.515 log(REC)/log(R): 0.319
Determinism: 0.939 Laminarity: 0.81
DIV: 0.027
Trend: 0 Entropy: 2.346
Diagonal lines max: 37 Mean: 5.373 Mean off main: 5.362
Vertical lines max: 48 Mean: 3.998
```

Dim=2. Time used: 2.318 sec.

Input

```
hrvRRVtakens6 <- local.buildTakens( time.series=HRRV[1:nSignal],
      embedding.dim=6, time.lag=1)
hrvRRVneighs6 <- local.findAllNeighbours(hrvRRVtakens6[-(1:2),], radius=0.125)
save(hrvRRVneighs6, file="hrvRRVneighs6.Rdata")
# load(file="hrvRRVneighs6.RData")
local.recurrencePlotAux(hrvRRVneighs6, dim=6, radius=0.125)
showrqa(hrvRRVtakens6[-(1:2),], radius=0.125, do.hist=FALSE)
```

Output

```
hrvRRVtakens6[-(1:2), ] n: 1017 Dim: 6
Radius: 0.125 Recurrence coverage REC: 0.179 log(REC)/log(R): 0.827
Determinism: 0.943 Laminarity: 0.451
DIV: 0.03
Trend: 0 Entropy: 2.305
Diagonal lines max: 33 Mean: 5.243 Mean off main: 5.213
Vertical lines max: 22 Mean: 2.887
```

Dim=6. Time used: 1.66 sec.

Input

```
hrvRRVtakens8 <- local.buildTakens( time.series=HRRV[1:nSignal],
      embedding.dim=8, time.lag=1)
hrvRRVneighs8 <- local.findAllNeighbours(hrvRRVtakens8[-(1:2),], radius=0.125)
save(hrvRRVneighs8, file="hrvRRVneighs8.Rdata")
# load(file="hrvRRVneighs8.RData")
local.recurrencePlotAux(hrvRRVneighs8, dim=8, radius=0.125)
showrqa(hrvRRVtakens8[-(1:2),], radius=0.125, do.hist=FALSE)
```

Output

```

hrvRRVtakens8[-(1:2), ] n: 1015 Dim: 8
Radius: 0.125 Recurrence coverage REC: 0.105 log(REC)/log(R): 1.084
Determinism: 0.943 Laminarity: 0.337
DIV: 0.032
Trend: 0 Entropy: 2.329
Diagonal lines max: 31 Mean: 5.361 Mean off main: 5.308
Vertical lines max: 17 Mean: 2.715

```

Dim=8. Time used: 1.28 sec.

Input

```

hrvRRVtakens12 <-
  local.buildTakens( time.series=HRRV[1:nseries],
                     embedding.dim=12, time.lag=1)
hrvRRVneighs12 <-
  local.findAllNeighbours(hrvRRVtakens12[-(1:2), ], radius=3/16)
save(hrvRRVneighs12, file="hrvRRVneighs12.Rdata")
# load(file="hrvRRVneighs12.RData")
local.recurrencePlotAux(hrvRRVneighs12, dim=12, radius=3/16)
showrqa(hrvRRVtakens12[-(1:2), ], radius=3/16, do.hist=FALSE)

```

Output

```

hrvRRVtakens12[-(1:2), ] n: 1011 Dim: 12
Radius: 0.1875 Recurrence coverage REC: 0.235 log(REC)/log(R): 0.865
Determinism: 0.988 Laminarity: 0.635
DIV: 0.015
Trend: 0 Entropy: 3.075
Diagonal lines max: 68 Mean: 9.775 Mean off main: 9.733
Vertical lines max: 52 Mean: 3.656

```

Dim=12: Time used: 1.715 sec.

Input

```

hrvRRVtakens16 <- local.buildTakens( time.series=HRRV[1:nseries],
                                         embedding.dim=16, time.lag=1)
hrvRRVneighs16 <- local.findAllNeighbours(hrvRRVtakens16[-(1:2), ], radius=3/16)
save(hrvRRVneighs16, file="hrvRRVneighs16.Rdata")
# load(file="hrvRRVneighs16.RData")
local.recurrencePlotAux(hrvRRVneighs16, dim=16, radius=3/16)
showrqa(hrvRRVtakens16[-(1:2), ], radius=3/16, do.hist=FALSE)

```

Output

```

hrvRRVtakens16[-(1:2), ] n: 1007 Dim: 16
Radius: 0.1875 Recurrence coverage REC: 0.147 log(REC)/log(R): 1.144
Determinism: 0.99 Laminarity: 0.527
DIV: 0.016
Trend: 0 Entropy: 3.163
Diagonal lines max: 64 Mean: 10.594 Mean off main: 10.523
Vertical lines max: 40 Mean: 3.114

```

Dim=16. Time used: 1.629 sec.

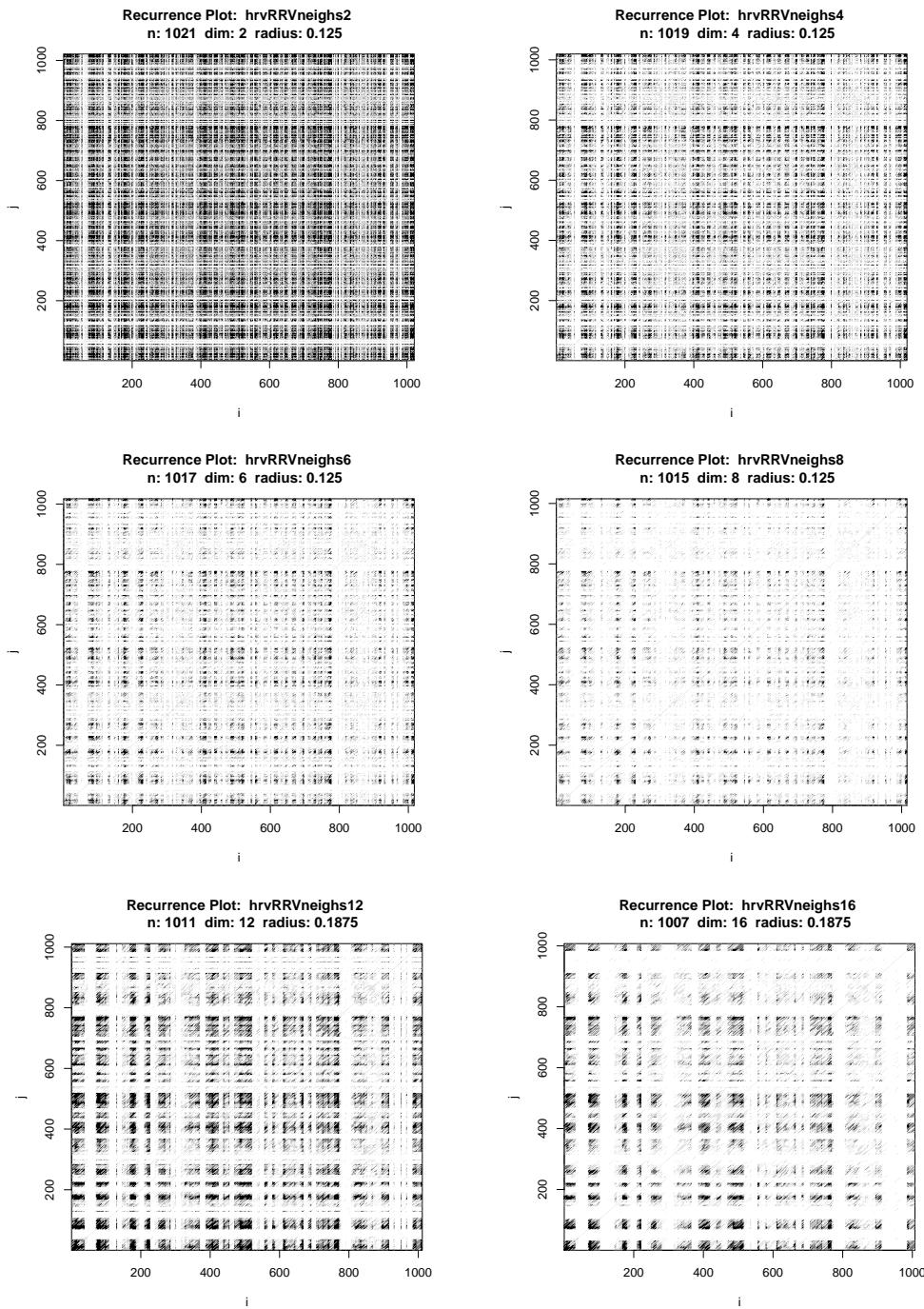


FIGURE 69. Recurrence Plot. Example case: RHRV tutorial example.beats variation. Dim=2, 4, 6, 8, 12, 16. Time used: 1.629 sec.

9.1.2. *RHRV: example.beats - RR Variation: Comparison by Dimension, Time.Lag = 8.*

Input

```
hrvRRVtakens2Lag08 <- local.buildTakens( time.series=HRRV[1:nsignal],
                                           embedding.dim=2, time.lag=8)
hrvRRVneighs2Lag08 <- local.findAllNeighbours(hrvRRVtakens2Lag08[-(1:2),],
                                                 radius=0.125)
save(hrvRRVneighs2Lag08, file="hrvRRVneighs2Lag08.Rdata")
# load(file="hrvRRVneighs2Lag08.RData")
local.recurrencePlotAux(hrvRRVneighs2Lag08, dim=2, radius=0.125)
showrqa(hrvRRVtakens2Lag08[-(1:2),], radius=0.125, do.hist=FALSE)
```

Output

```
hrvRRVtakens2Lag08[-(1:2), ] n: 1014 Dim: 2
Radius: 0.125 Recurrence coverage REC: 0.469 log(REC)/log(R): 0.364
Determinism: 0.809 Laminarity: 0.792
DIV: 0.033
Trend: 0 Entropy: 1.637
Diagonal lines max: 30 Mean: 3.451 Mean off main: 3.442
Vertical lines max: 41 Mean: 3.445
```

Dim=2. Time used: 2.566 sec.

Input

```
hrvRRVtakens4Lag08 <- local.buildTakens( time.series=HRRV[1:nsignal],
                                           embedding.dim=4, time.lag=8)
hrvRRVneighs4Lag08 <- local.findAllNeighbours(hrvRRVtakens4Lag08[-(1:2),],
                                                 radius=0.125)
save(hrvRRVneighs4Lag08, file="hrvRRVneighs4Lag08.Rdata")
# load(file="hrvRRVneighs4Lag08.RData")
local.recurrencePlotAux(hrvRRVneighs4Lag08, dim=2, radius=0.125)
showrqa(hrvRRVtakens2Lag08[-(1:2),], radius=0.125, do.hist=FALSE)
```

Output

```
hrvRRVtakens2Lag08[-(1:2), ] n: 1014 Dim: 2
Radius: 0.125 Recurrence coverage REC: 0.469 log(REC)/log(R): 0.364
Determinism: 0.809 Laminarity: 0.792
DIV: 0.033
Trend: 0 Entropy: 1.637
Diagonal lines max: 30 Mean: 3.451 Mean off main: 3.442
Vertical lines max: 41 Mean: 3.445
```

Dim=4. Time used: 1.86 sec.

Input

```
statepairs(hrvRRVtakens4Lag08)
```

Input

```
statecplot(hrvRRVtakens4Lag08)
```

Output

```
Missing rows: 1, 2
```

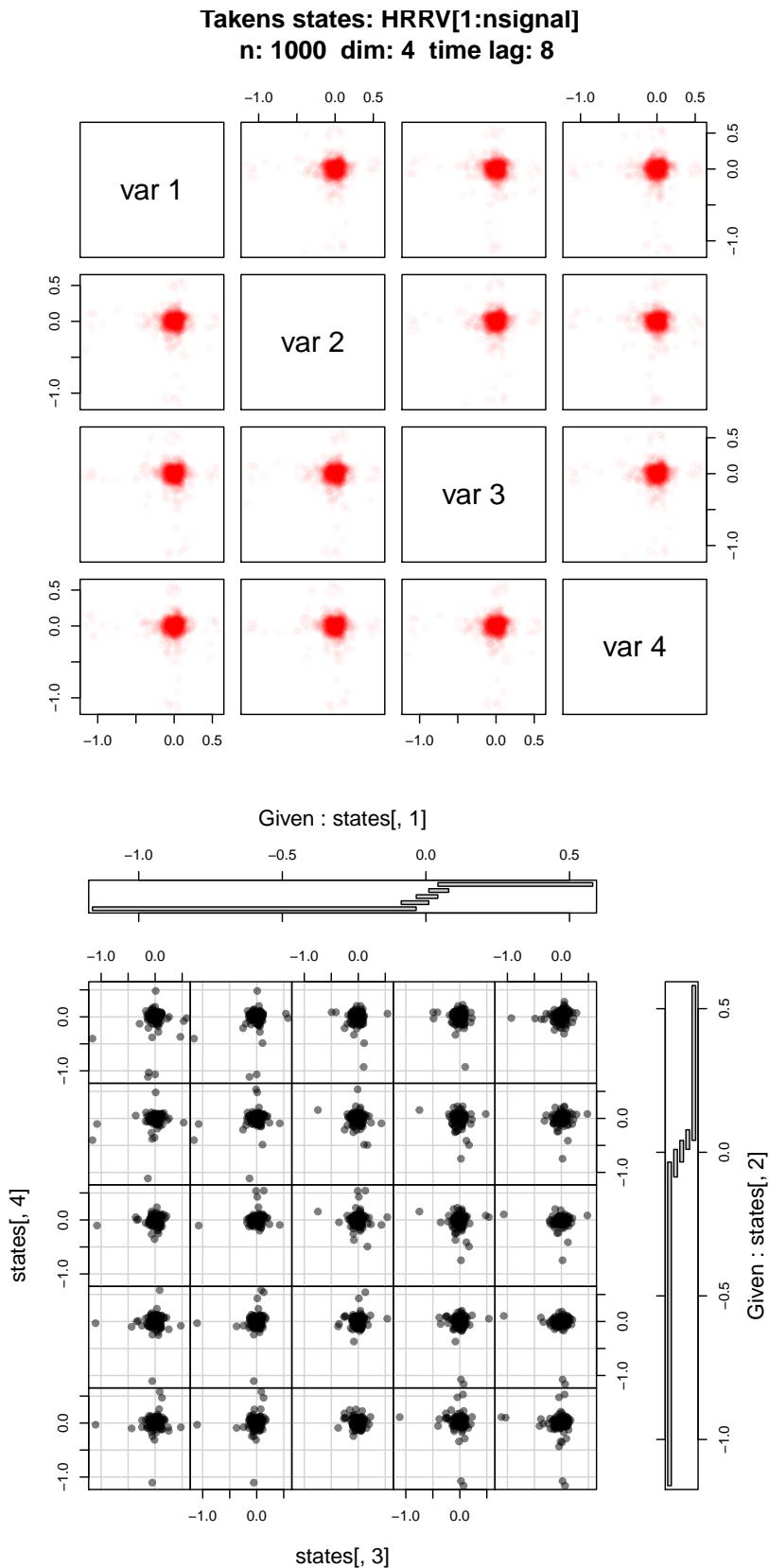


FIGURE 70. Takens states. Example case: RHRV tutorial example.beats variation. Dim=4, time.lag=8. Time used: 2.812 sec.

Input

```
statepairs(hrvRRVtakens4Lag08, range=c(-0.5, 0.5))
```

Input

```
statecoplot(hrvRRVtakens4Lag08, range=c(-0.5, 0.5))
```

Output

```
Missing rows: 1, 2, 38, 39, 46, 47, 54, 55, 62, 63, 100, 101, 102, 108, 109, 110, 116, 117, 118, 124, 125
```

Input

```
hrvRRVtakens6Lag08 <- local.buildTakens( time.series=HRRV[1:nsignal],
                                             embedding.dim=6, time.lag=8)
hrvRRVneighs6Lag08 <- local.findAllNeighbours(hrvRRVtakens6Lag08[-(1:2),], radius=0.125)
save(hrvRRVneighs6Lag08, file="hrvRRVneighs6Lag08.Rdata")
# load(file="hrvRRVneighs6Lag08.RData")
local.recurrencePlotAux(hrvRRVneighs6Lag08, dim=6, radius=0.125)
showrqa(hrvRRVtakens6Lag08[-(1:2),], radius=0.125, do.hist=FALSE)
```

Output

```
hrvRRVtakens6Lag08[-(1:2), ] n: 982 Dim: 6
Radius: 0.125 Recurrence coverage REC: 0.1 log(REC)/log(R): 1.107
Determinism: 0.357 Laminarity: 0.311
DIV: 0.143
Trend: 0 Entropy: 0.604
Diagonal lines max: 7 Mean: 2.302 Mean off main: 2.237
Vertical lines max: 8 Mean: 2.234
```

Dim=6. Time used: 4.84 sec.

Input

```
hrvRRVtakens8Lag08 <- local.buildTakens( time.series=HRRV[1:nsignal],
                                             embedding.dim=8, time.lag=8)
hrvRRVneighs8Lag08 <- local.findAllNeighbours(hrvRRVtakens8Lag08[-(1:2),], radius=0.125)
save(hrvRRVneighs8Lag08, file="hrvRRVneighs8Lag08.Rdata")
# load(file="hrvRRVneighs8Lag08.RData")
local.recurrencePlotAux(hrvRRVneighs8Lag08, dim=8, radius=0.125)
showrqa(hrvRRVtakens8Lag08[-(1:2),], radius=0.125, do.hist=FALSE)
```

Output

```
hrvRRVtakens8Lag08[-(1:2), ] n: 966 Dim: 8
Radius: 0.125 Recurrence coverage REC: 0.045 log(REC)/log(R): 1.488
Determinism: 0.223 Laminarity: 0.161
DIV: 0.2
Trend: 0 Entropy: 0.354
Diagonal lines max: 5 Mean: 2.348 Mean off main: 2.108
Vertical lines max: 5 Mean: 2.089
```

Dim=8. Time used: 0.922 sec.

Input

```
hrvRRVtakens12Lag08 <-
  local.buildTakens( time.series=HRRV[1:nsignal],
                     embedding.dim=12, time.lag=8)
hrvRRVneighs12Lag08 <-
```

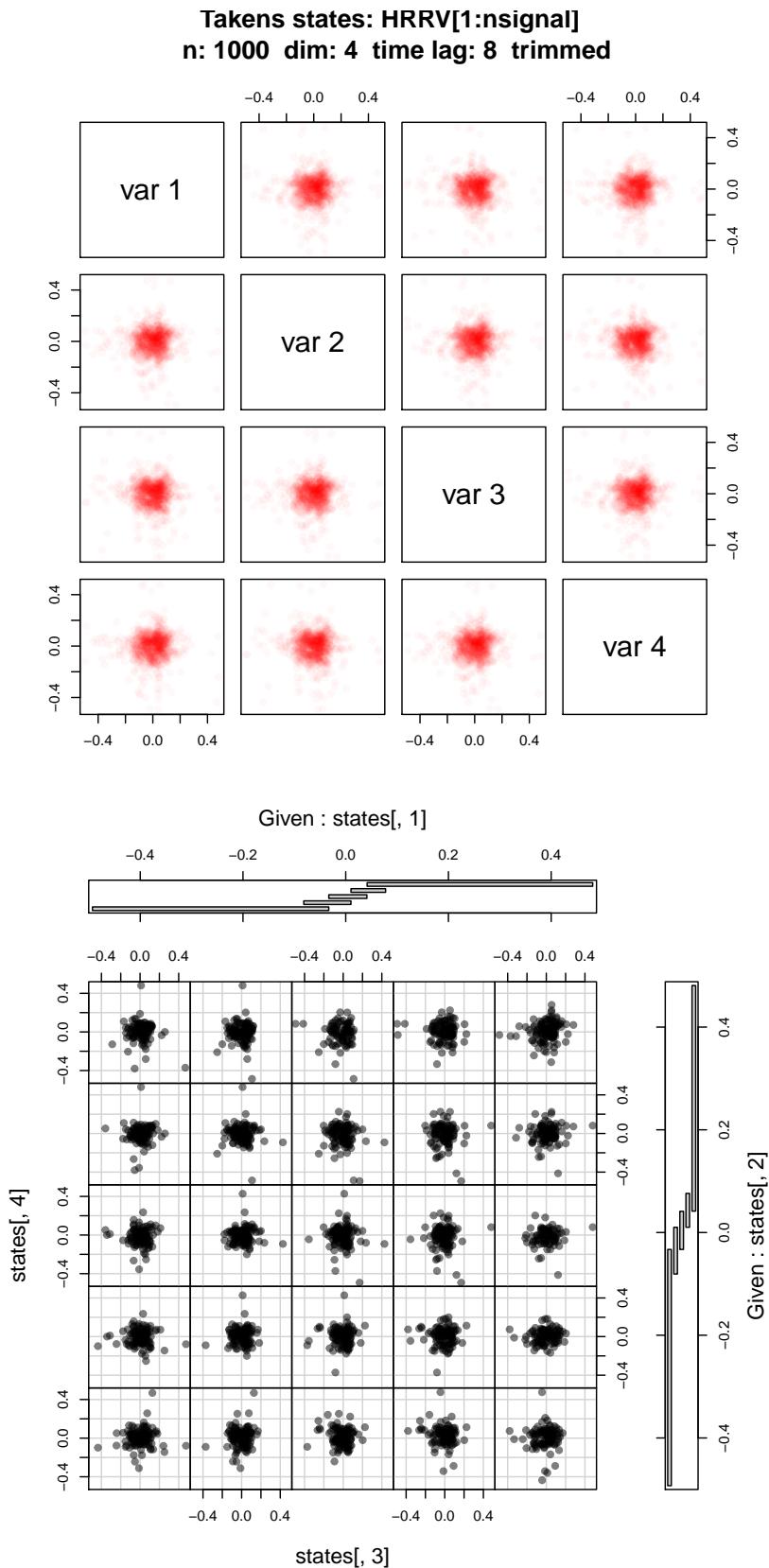


FIGURE 71. Takens states. Example case: RHRV tutorial example.beats variation, trimmed. Dim=4, time.lag=8. Time used: 3.653 sec.

```

local.findAllNeighbours(hrvRRVtakens12Lag08[-(1:2),], radius=3/16)
save(hrvRRVneighs12Lag08, file="hrvRRVneighs12Lag08.Rdata")
# load(file="hrvRRVneighs12Lag08.RData")
local.recurrencePlotAux(hrvRRVneighs12Lag08, dim=12, radius=3/16)
showrqa(hrvRRVtakens12Lag08[-(1:2),], radius=3/16, do.hist=FALSE)

```

<hr/>	Output	<hr/>
hrvRRVtakens12Lag08[-(1:2),] n: 934 Dim: 12		
Radius: 0.1875 Recurrence coverage REC: 0.133 log(REC)/log(R): 1.207		
Determinism: 0.472 Laminarity: 0.443		
DIV: 0.143		
Trend: 0 Entropy: 0.77		
Diagonal lines max: 7 Mean: 2.39 Mean off main: 2.349		
Vertical lines max: 7 Mean: 2.457		

Dim=12: Time used: 1.341 sec.

<hr/>	Input	<hr/>
hrvRRVtakens16Lag08 <- local.buildTakens(time.series=HRRV[1:nsignal],		
embedding.dim=16, time.lag=8)		
hrvRRVneighs16Lag08 <- local.findAllNeighbours(hrvRRVtakens16Lag08[-(1:2),], radius=3/16)		
save(hrvRRVneighs16Lag08, file="hrvRRVneighs16Lag08.Rdata")		
# load(file="hrvRRVneighs16Lag08.RData")		
local.recurrencePlotAux(hrvRRVneighs16Lag08, dim=16, radius=3/16)		
showrqa(hrvRRVtakens16Lag08[-(1:2),], radius=3/16, do.hist=FALSE)		

<hr/>	Output	<hr/>
hrvRRVtakens16Lag08[-(1:2),] n: 902 Dim: 16		
Radius: 0.1875 Recurrence coverage REC: 0.071 log(REC)/log(R): 1.581		
Determinism: 0.339 Laminarity: 0.31		
DIV: 0.167		
Trend: 0 Entropy: 0.608		
Diagonal lines max: 6 Mean: 2.347 Mean off main: 2.239		
Vertical lines max: 6 Mean: 2.321		

Dim=16. Time used: 1.022 sec.

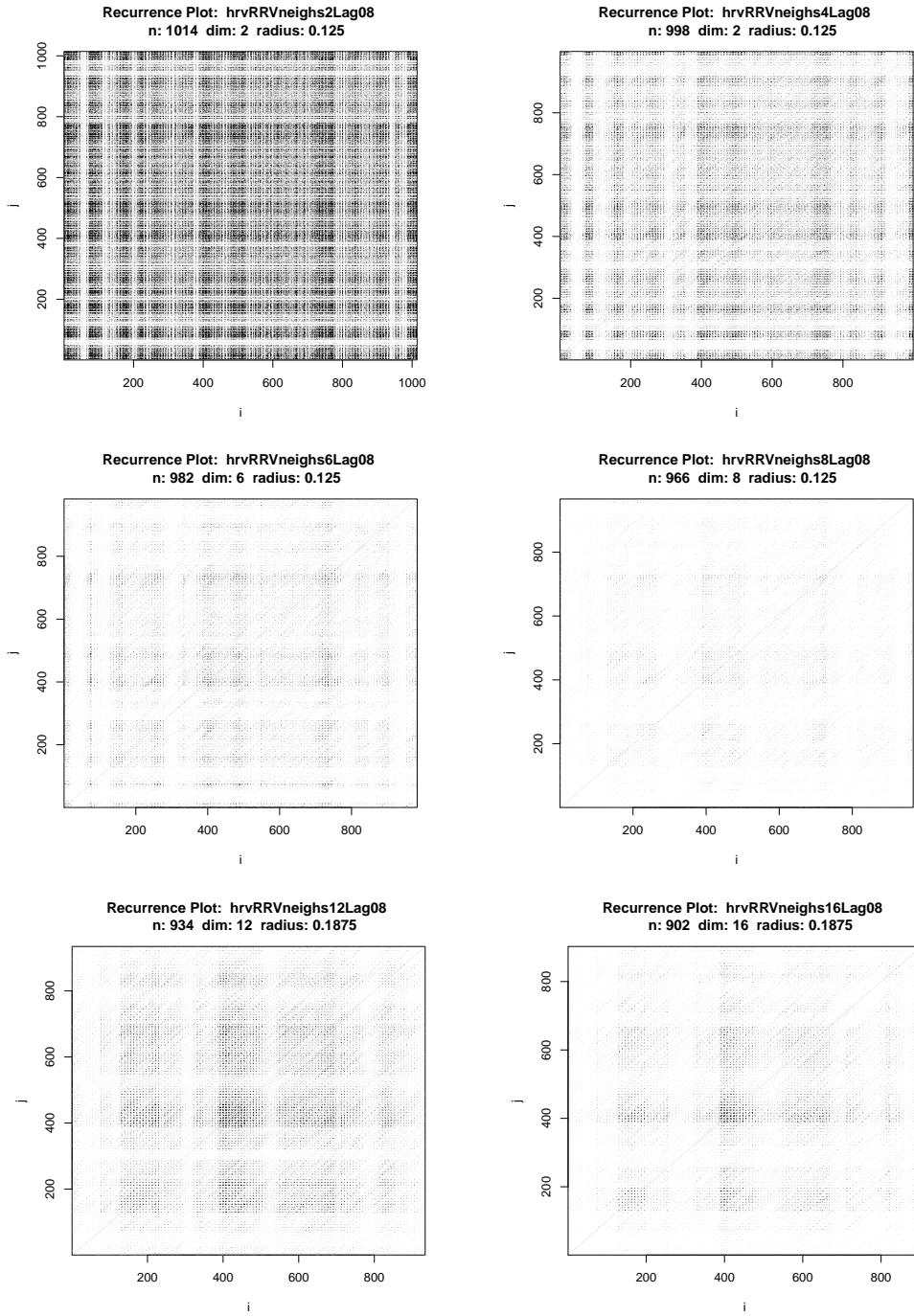


FIGURE 72. Recurrence Plot. Example case: RHRV tutorial example.beats variation. Dim=2, 4, 6, 8, 12, 16. Time.lag=8. Time used: 1.022 sec.

10. CASE STUDY: HRV DATA EXAMPLE2.BEATS

This is a copy of the previous section, now applied to HRV data example2.beats.

Input

```

library(RHRV)
load("/users/gs/projects/rforge/rhrv/pkg/data/HRVData.rda")
load("/users/gs/projects/rforge/rhrv/pkg/data/HRVProcessedData.rda")
#####
### code chunk number 1: creation
#####
hrv2.data = CreateHRVData()
hrv2.data = SetVerbose(hrv2.data, TRUE )
#####
### code chunk number 3: loading
#####
hrv2.data = LoadBeatAscii(hrv2.data, "example2.beats",
    RecordPath = "/users/gs/projects/rforge/rhrv/tutorial/beatsFolder")
#      RecordPath = "beatsFolder")

#####
### code chunk number 4: derivating
#####
hrv2.data = BuildNIHR(hrv2.data)

```

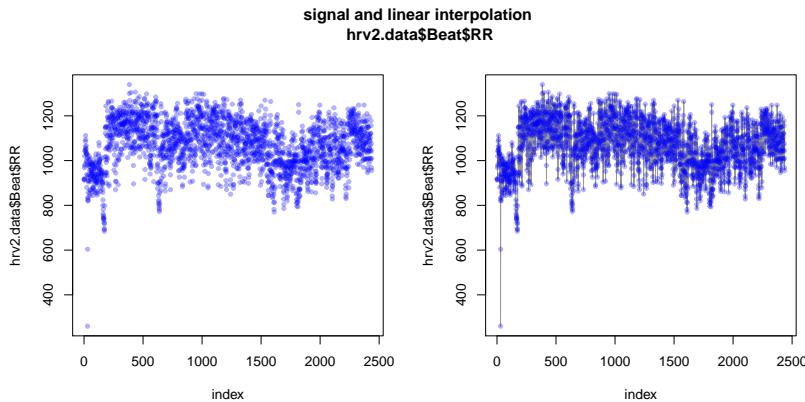
Input

```

plotsignal(hrv2.data$Beat$RR)

```

See Figure 73.



ToDo: We have outliers at approximately $2 \times \text{RR}$. Could this be an artefact of preprocessing, filtering out too many impulses?

FIGURE 73. RHRV tutorial example2.beats. Signal and linear interpolation.

Input

```

hrv2RRtakens4 <- local.buildTakens( time.series=hrv2.data$Beat$RR[1:nSignal],
    embedding.dim=4, time.lag=1)
statepairs(hrv2RRtakens4) #dim=4

```

See Figure 74 on the next page.

Only 1024 data points used in this plot

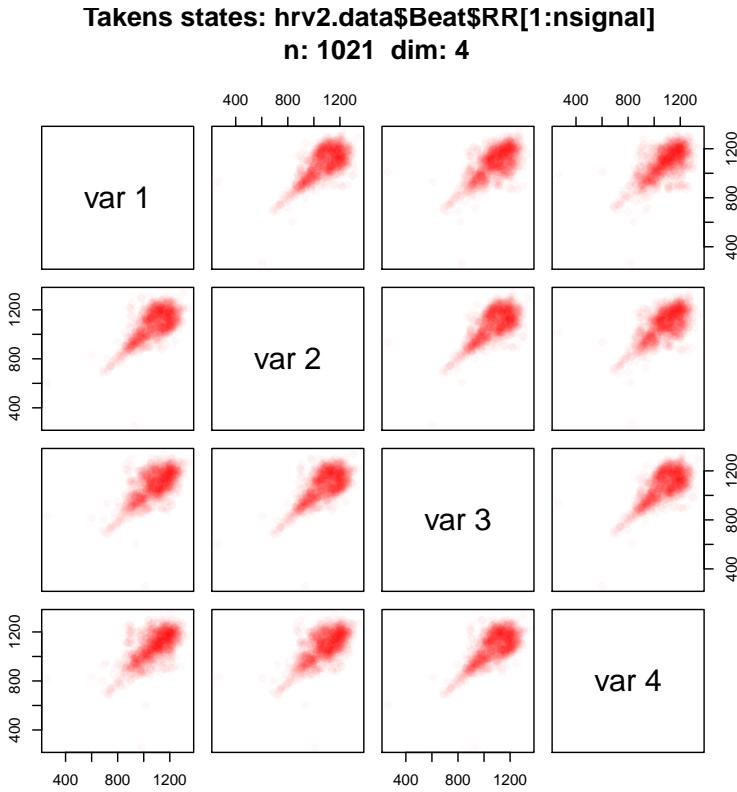


FIGURE 74. RHRV tutorial example2.beats. Time used: 0.7 sec.

Input
`statepairs(hrv2RRTakens4, rank=TRUE) #dim=4`

See Figure 75 on the facing page.

Input
`statecoplot(hrv2RRTakens4) #dim=4`

See Figure 76 on page 104.

Input
`hrv2RRneighs4 <- local.findAllNeighbours(hrv2RRTakens4, radius=12*16)
save(hrv2RRneighs4, file="hrv2Rneighs4.Rdata")
load(file="hrv2Rneighs4.RData")
local.recurrencePlotAux(hrv2RRneighs4, radius=12*16)
showrqa(hrv2RRTakens4[-(1:2),], radius=12*16, do.hist=FALSE)`

Output
`hrv2RRTakens4[-(1:2),] n: 1019 Dim: 4
Radius: 192 Recurrence coverage REC: 0.493 log(REC)/log(R): -0.135
Determinism: 0.982 Laminarity: 0.906
DIV: 0.005
Trend: 0 Entropy: 3.158
Diagonal lines max: 191 Mean: 10.396 Mean off main: 10.375
Vertical lines max: 136 Mean: 7.145`

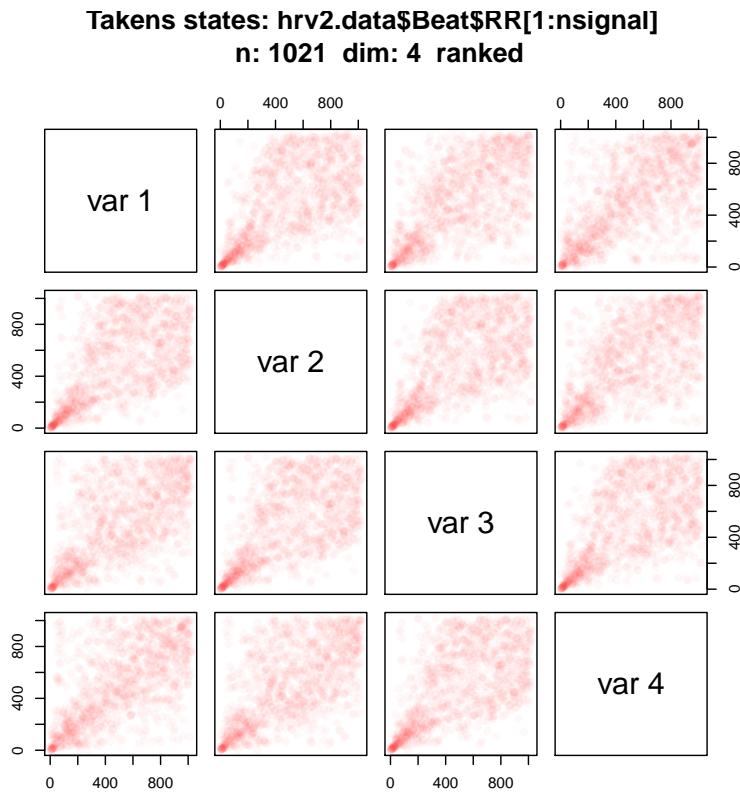


FIGURE 75. RHRV tutorial example2.beats. Ranked data. Time used:
1.404 sec.

Dim=4. Time used: 2.44 sec.

See Figure 77 on page 105.

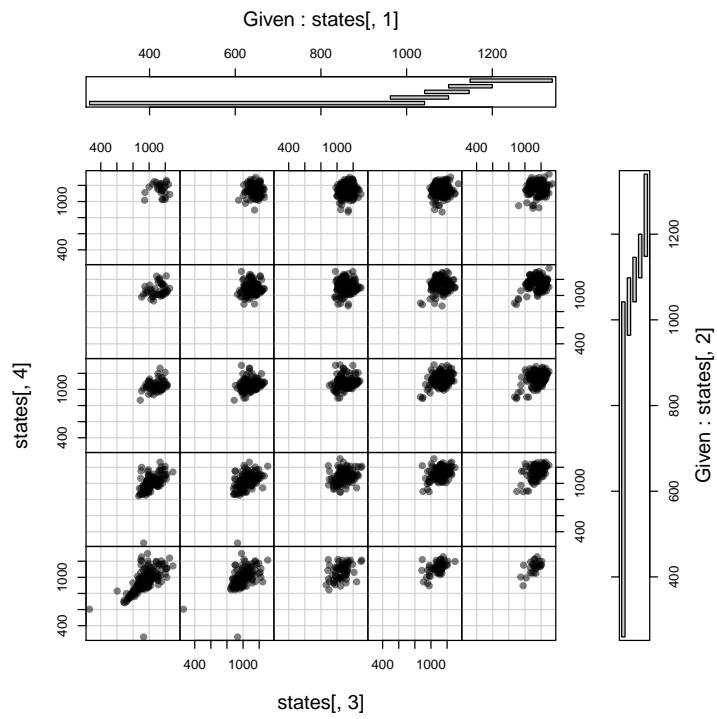


FIGURE 76. State coplot. RHRV tutorial example2.beats. Time used:
0.262 sec.

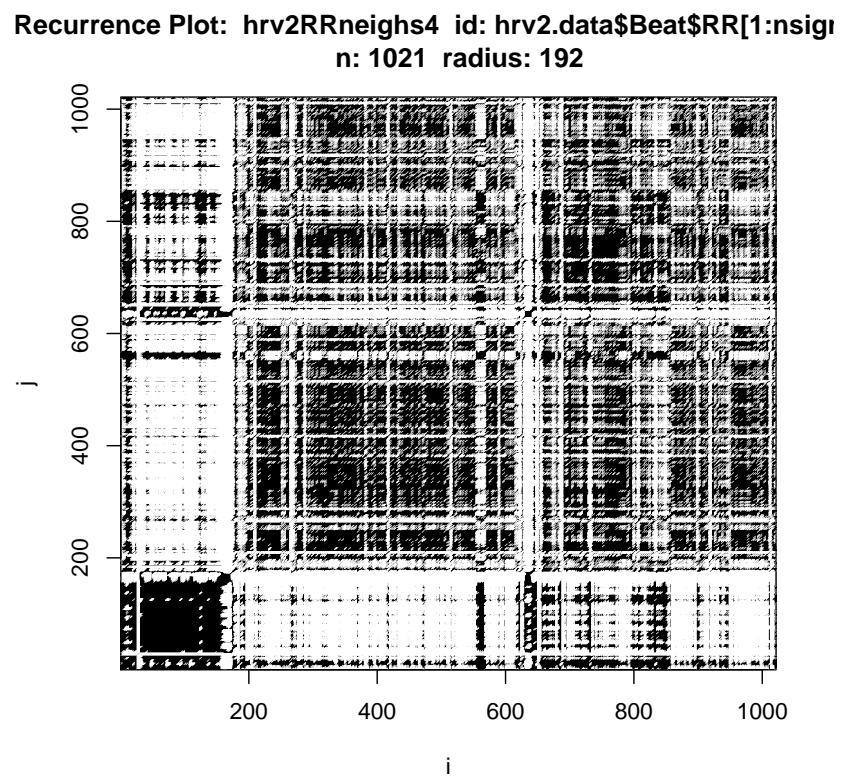


FIGURE 77. Recurrence Plot. Example case: RHRV tutorial example2.beats. Dim=4. Time used: 2.44 sec.

We should expect the breathing rhythm, so a time lag in the order of 10 is to be expected.

10.0.1. RHRV: *example2.beats*, RR-intervals. Comparison by Dimension.

```
Input
hrv2RRtakens2 <- local.buildTakens( time.series=hrv2.data$Beat$RR[1:nsignal],
  embedding.dim=2, time.lag=1)
hrv2RRneighs2 <- local.findAllNeighbours(hrv2RRtakens2, radius=10*16)
save(hrv2RRneighs2, file="hrv2RRneighs2.Rdata")
# load(file="hrv2RRneighs2.RData")
local.recurrencePlotAux(hrv2RRneighs2, radius=10*16)
showrqa(hrv2RRtakens2[-(1:2),], radius=10*16, do.hist=FALSE)
```

```
Output
hrv2RRtakens2[-(1:2), ] n: 1021 Dim: 2
Radius: 160 Recurrence coverage REC: 0.52 log(REC)/log(R): -0.129
Determinism: 0.948 Laminarity: 0.91
DIV: 0.007
Trend: 0 Entropy: 2.691
Diagonal lines max: 152 Mean: 7.057 Mean off main: 7.043
Vertical lines max: 130 Mean: 6.607
```

Dim=2. Time used: 2.389 sec.

See Figure 78 on page 108.

```
Input
hrv2RRtakens6 <- local.buildTakens( time.series=hrv2.data$Beat$RR[1:nsignal],
  embedding.dim=6, time.lag=1)
hrv2RRneighs6 <- local.findAllNeighbours(hrv2RRtakens6, radius=14*16)
save(hrv2RRneighs6, file="hrv2RRneighs6.Rdata")
# load(file="hrv2RRneighs6.RData")
local.recurrencePlotAux(hrv2RRneighs6, radius=14*16)
showrqa(hrv2RRtakens6[-(1:2),], radius=14*16, do.hist=FALSE)
```

```
Output
hrv2RRtakens6[-(1:2), ] n: 1017 Dim: 6
Radius: 224 Recurrence coverage REC: 0.528 log(REC)/log(R): -0.118
Determinism: 0.993 Laminarity: 0.925
DIV: 0.004
Trend: 0 Entropy: 3.584
Diagonal lines max: 225 Mean: 15.258 Mean off main: 15.23
Vertical lines max: 167 Mean: 9.007
```

Dim=6. Time used: 2.604 sec.

See Figure 78 on page 108.

```
Input
hrv2RRtakens8 <- local.buildTakens( time.series=hrv2.data$Beat$RR[1:nsignal],
  embedding.dim=8, time.lag=1)
hrv2RRneighs8 <- local.findAllNeighbours(hrv2RRtakens8, radius=16*16)
save(hrv2RRneighs8, file="hrv2RRneighs8.Rdata")
# load(file="hrv2RRneighs8.RData")
local.recurrencePlotAux(hrv2RRneighs8, radius=16*16)
showrqa(hrv2RRtakens8[-(1:2),], radius=16*16, do.hist=FALSE)
```

<pre>hrv2RRtakens8[-(1:2),] n: 1015 Dim: 8</pre>	<i>Output</i>
Radius: 256 Recurrence coverage REC: 0.584 log(REC)/log(R): -0.097	
Determinism: 0.997 Laminarity: 0.942	
DIV: 0.004	
Trend: 0 Entropy: 3.986	
Diagonal lines max: 241 Mean: 22.506 Mean off main: 22.469	
Vertical lines max: 310 Mean: 11.256	

Dim=8. Time used: 2.753 sec.

See Figure 78 on the next page.

<pre>hrv2RRtakens12 <- local.buildTakens(time.series=hrv2.data\$Beat\$RR[1:nsignal],</pre>	<i>Input</i>
<pre>embedding.dim=12, time.lag=1)</pre>	
<pre>hrv2RRneighs12 <- local.findAllNeighbours(hrv2RRtakens12, radius=16*16)</pre>	
<pre>save(hrv2RRneighs12, file="hrv2RRneighs12.Rdata")</pre>	
<pre># load(file="hrv2RRneighs12.RData")</pre>	
<pre>local.recurrencePlotAux(hrv2RRneighs12, radius=16*16)</pre>	
<pre>showrqa(hrv2RRtakens12[-(1:2),], radius=16*16, do.hist=FALSE)</pre>	

<pre>hrv2RRtakens12[-(1:2),] n: 1011 Dim: 12</pre>	<i>Output</i>
Radius: 256 Recurrence coverage REC: 0.488 log(REC)/log(R): -0.129	
Determinism: 0.997 Laminarity: 0.914	
DIV: 0.004	
Trend: 0 Entropy: 4.062	
Diagonal lines max: 237 Mean: 24.127 Mean off main: 24.079	
Vertical lines max: 299 Mean: 8.972	

Dim=12. Time used: 2.381 sec.

<pre>hrv2RRtakens16 <- local.buildTakens(</pre>	<i>Input</i>
<pre>time.series=hrv2.data\$Beat\$RR[1:nsignal],</pre>	
<pre>embedding.dim=16, time.lag=1)</pre>	
<pre>hrv2RRneighs16 <- local.findAllNeighbours(hrv2RRtakens16, radius=18*16)</pre>	
<pre>save(hrv2RRneighs16, file="hrv2RRneighs16.Rdata")</pre>	
<pre># load(file="hrv2RRneighs16.RData")</pre>	
<pre>local.recurrencePlotAux(hrv2RRneighs16, radius=18*16)</pre>	
<pre>showrqa(hrv2RRtakens16[-(1:2),], radius=18*16, do.hist=FALSE)</pre>	

<pre>hrv2RRtakens16[-(1:2),] n: 1007 Dim: 16</pre>	<i>Output</i>
Radius: 288 Recurrence coverage REC: 0.544 log(REC)/log(R): -0.107	
Determinism: 0.999 Laminarity: 0.932	
DIV: 0.003	
Trend: 0 Entropy: 4.372	
Diagonal lines max: 346 Mean: 34.916 Mean off main: 34.854	
Vertical lines max: 297 Mean: 9.929	

Dim=16. Time used: 2.635 sec.

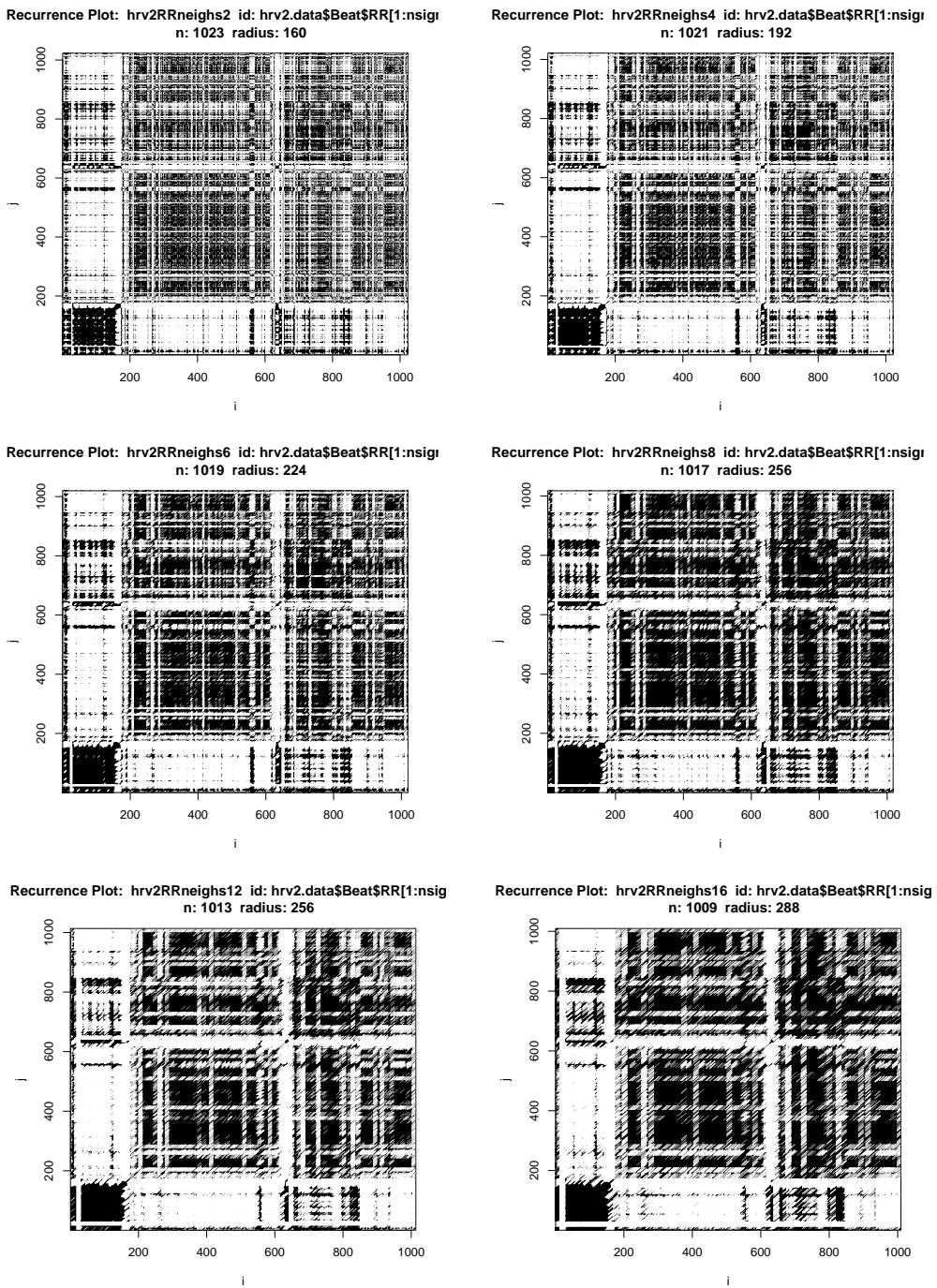


FIGURE 78. Recurrence Plot. Example case: RHRV tutorial example2.beats. Dim=2, 4, 6, 8, 12, 16. Time used: 2.635 sec.

10.1. RHRV: example2.beats - Hart Rate Variation. Since we are not interested in heart rate (or pulse), but in heart rate variation, a proposal is to use scaled differences.

ToDo: Consider using differences
differences for HRV

Input

```
hrv2.data <- BuildNIDHR(hrv2.data)
```

Output

```
** Calculating non-interpolated heart rate differences **
Number of beats: 2437
```

Input

```
HRRV <- hrv2.data$Beat$HRRV
```

These are the displays of the Takens state space we used before, now for HRRV:

Input

```
plotsignal(HRRV)
```

See Figure 79,

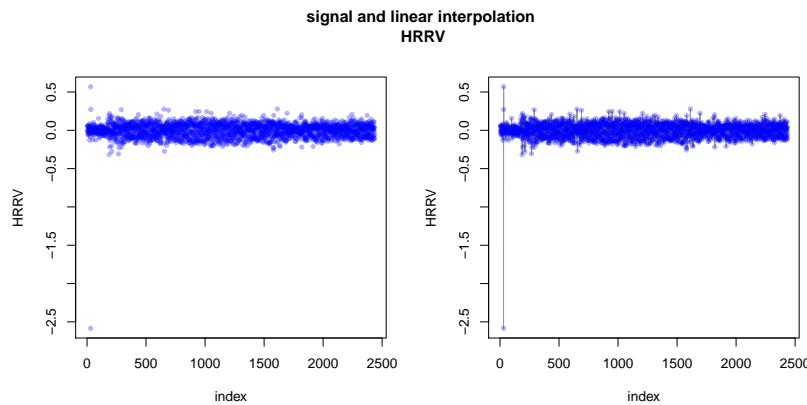


FIGURE 79. RHRV tutorial example2.beats. HRRV Signal and linear interpolation.

Only 1024 data points used in these plots

Input

```
hrv2RRVtakens4 <-
  local.buildTakens( time.series=HRRV[1:nseries],
                     embedding.dim=4,time.lag=1)
statepairs(hrv2RRVtakens4) #dim=4
```

See Figure 80 on the next page.

Input

```
statecoplot(hrv2RRVtakens4) #dim=4
```

Output

```
Missing rows: 1, 2
```

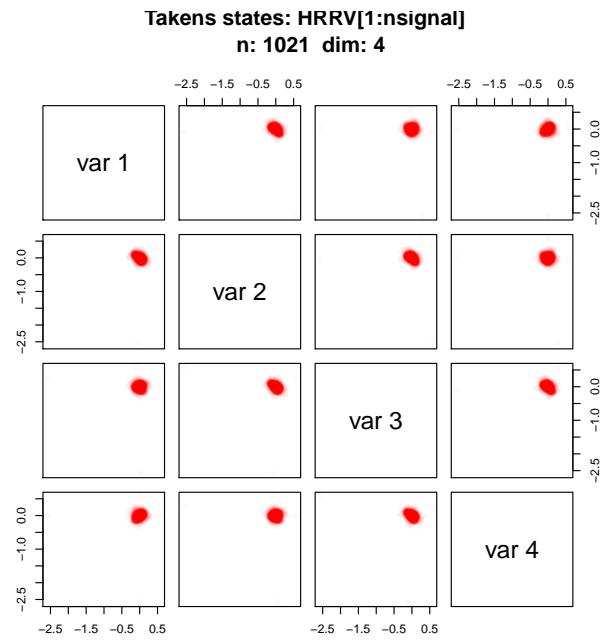


FIGURE 80. Recurrence plot. RHRV tutorial example2.beats. HRRV.
Time used: 0.771 sec.

See Figure 81.

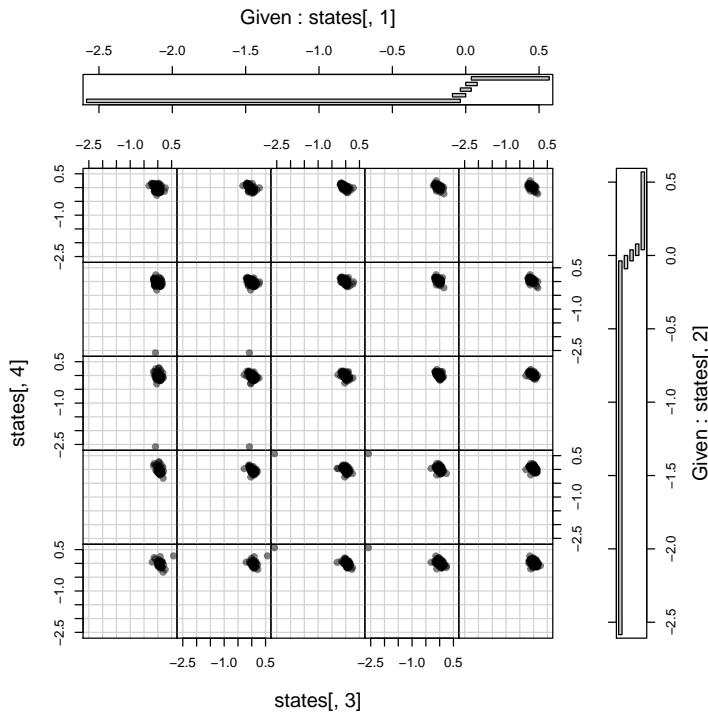


FIGURE 81. State coplot. RHRV tutorial example2.beats. HRRV. Time
used: 0.987 sec.

Input

```
statepairs(hrv2RRVtakens4, rank=TRUE) #dim=4
```

See Figure 82

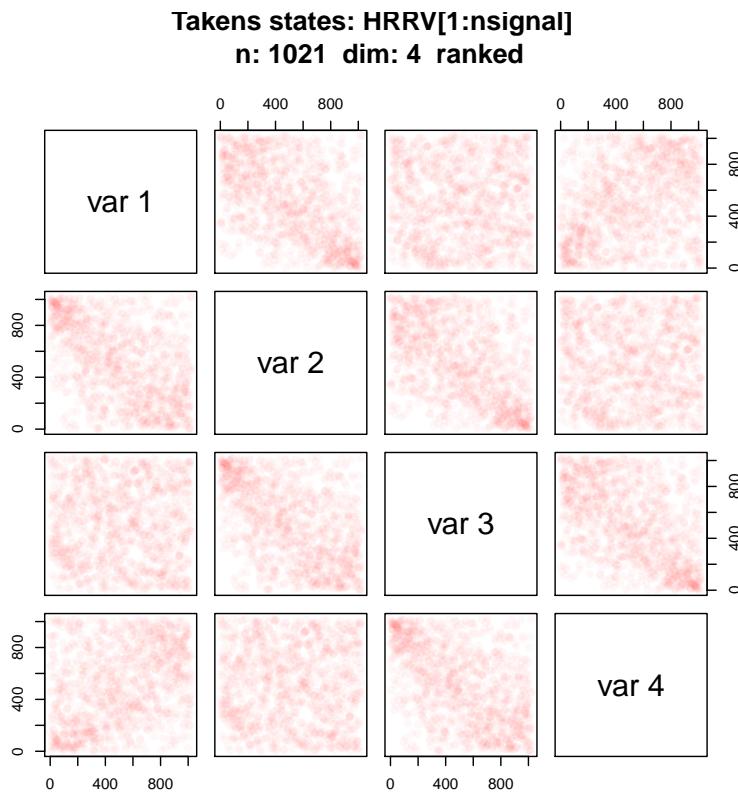


FIGURE 82. RHRV tutorial example2.beats. Ranked HRRV data. Time used: 1.716 sec.

Input

```
hrv2RRVtakens41 <- hrv2RRVtakens4
hrv2RRVtakens41[hrv2RRVtakens41 < -1.5] <- NA
hrv2RRVtakens41[hrv2RRVtakens41 > 0.45] <- NA
statepairs(hrv2RRVtakens41) #dim=4
```

See Figure 83 on the following page.

Input

```
statecoplot(hrv2RRVtakens41) #dim=4
```

Output

```
Missing rows: 1, 2, 27, 28, 29, 30, 31
```

See Figure 84 on the next page.

To Do: findAllNeighbours does not handle NAs

Input

```
#use hack: findAllNeighbours does not handle NAs
hrv2RRVneighs4 <- local.findAllNeighbours(hrv2RRVtakens4[-(1:2),], radius=0.125)
save(hrv2RRVneighs4, file="hrv2RRVneighs4.Rdata")
```

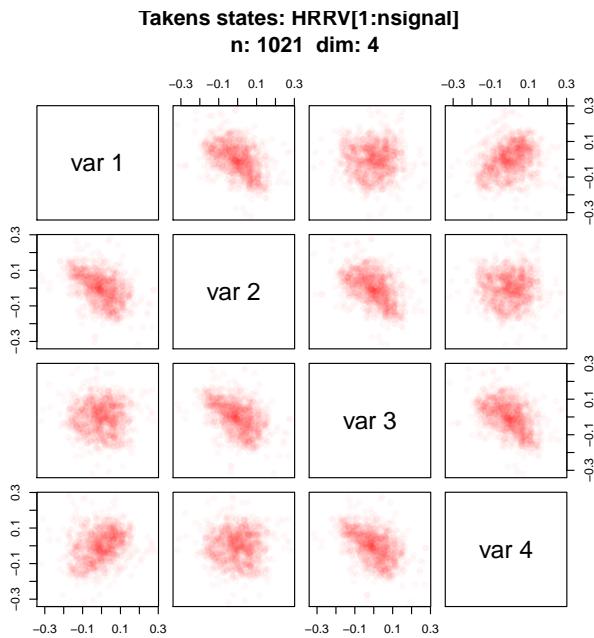


FIGURE 83. Recurrence plot. RHRV tutorial example2.beats. HRRV.
Time used: 2.396 sec.

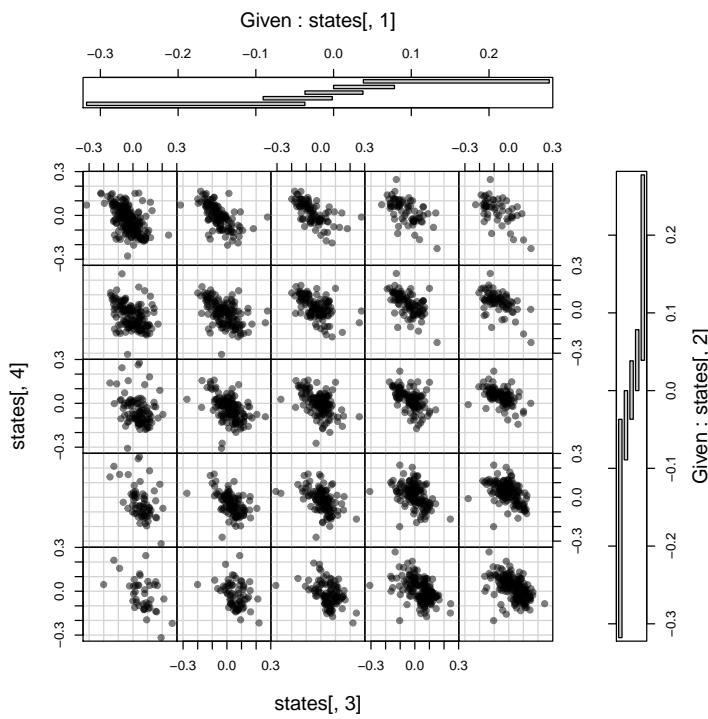


FIGURE 84. State coplot. RHRV tutorial example2.beats. HRRV. Time
used: 2.63 sec.

Time used: 0.163 sec.

Input

```
load(file="hrv2RRVneighs4.RData")
local.recurrencePlotAux(hrv2RRVneighs4, dim=4, radius=0.125)
```

ToDo: check. There seem to be strange artefacts.

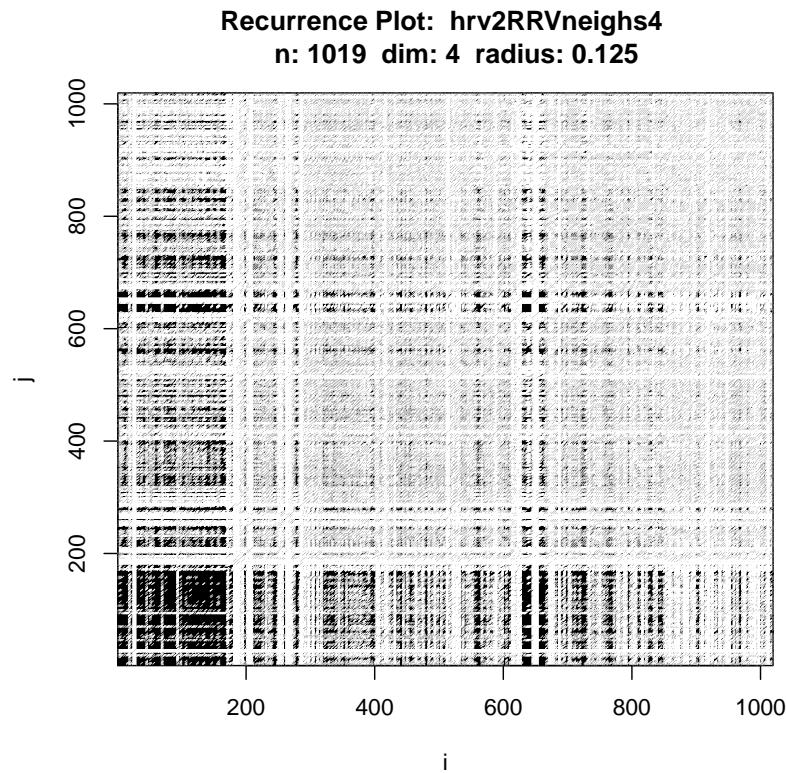


FIGURE 85. Recurrence Plot. Example case: RHRV tutorial example2.beats. HRRV Dim=4. Time used: 1.278 sec.

We should expect the breathing rhythm, so a time lag in the order of 10 beats is to be expected for the base signal.
ToDo: fix default setting for radius. Eckmann uses nearest neighbours with NN=10

10.1.1. RHRV: example2.beats - RR Variation: Comparison by Dimension.

```
Input
hrv2RRVtakens2 <- local.buildTakens( time.series=HRRV[1:nSignal],
                                         embedding.dim=2, time.lag=1)
hrv2RRVneighs2 <- local.findAllNeighbours(hrv2RRVtakens2[-(1:2), ],
                                              radius=0.125)
save(hrv2RRVneighs2, file="hrv2RRVneighs2.Rdata")
# load(file="hrv2RRVneighs2.RData")
local.recurrencePlotAux(hrv2RRVneighs2, dim=2, radius=0.125)
hrv2RRVrqa2 <- showrqa(hrv2RRVtakens2[-(1:2), ], radius=0.125, do.hist=FALSE)
```

```
Output
hrv2RRVtakens2[-(1:2), ] n: 1021 Dim: 2
Radius: 0.125 Recurrence coverage REC: 0.508 log(REC)/log(R): 0.326
Determinism: 0.913 Laminarity: 0.712
DIV: 0.009
Trend: 0 Entropy: 2.289
Diagonal lines max: 117 Mean: 5.305 Mean off main: 5.294
Vertical lines max: 86 Mean: 3.923
```

Time used: 2.514 sec.

```
Input
hrv2RRVtakens6 <- local.buildTakens( time.series=HRRV[1:nSignal],
                                         embedding.dim=6, time.lag=1)
hrv2RRVneighs6 <- local.findAllNeighbours(hrv2RRVtakens6[-(1:2), ], radius=0.125*1.5)
save(hrv2RRVneighs6, file="hrv2RRVneighs6.Rdata")
# load(file="hrv2RRVneighs6.RData")
local.recurrencePlotAux(hrv2RRVneighs6, dim=6, radius=0.125*1.5)
hrv2RRVrqa6 <- showrqa(hrv2RRVtakens6[-(1:2), ], radius=0.125*1.5, do.hist=FALSE)
```

```
Output
hrv2RRVtakens6[-(1:2), ] n: 1017 Dim: 6
Radius: 0.1875 Recurrence coverage REC: 0.516 log(REC)/log(R): 0.395
Determinism: 0.992 Laminarity: 0.736
DIV: 0.007
Trend: 0 Entropy: 3.355
Diagonal lines max: 147 Mean: 12.475 Mean off main: 12.452
Vertical lines max: 193 Mean: 4.902
```

Dim=6. Time used: 2.611 sec.

```
Input
hrv2RRVtakens8 <- local.buildTakens( time.series=HRRV[1:nSignal],
                                         embedding.dim=8, time.lag=1)
hrv2RRVneighs8 <- local.findAllNeighbours(hrv2RRVtakens8[-(1:2), ], radius=3/16)
save(hrv2RRVneighs8, file="hrv2RRVneighs8.Rdata")
# load(file="hrv2RRVneighs8.RData")
local.recurrencePlotAux(hrv2RRVneighs8, dim=8, radius=3/16)
hrv2RRVrqa8 <- showrqa(hrv2RRVtakens8[-(1:2), ], radius=3/16, do.hist=FALSE)
```

Output

```

hrv2RRVtakens8[-(1:2), ] n: 1015 Dim: 8
Radius: 0.1875 Recurrence coverage REC: 0.432 log(REC)/log(R): 0.501
Determinism: 0.992 Laminarity: 0.679
DIV: 0.007
Trend: 0 Entropy: 3.369
Diagonal lines max: 145 Mean: 12.714 Mean off main: 12.685
Vertical lines max: 147 Mean: 4.628

```

Dim=8. Time used: 2.252 sec.

Input

```

hrv2RRVtakens12 <-
  local.buildTakens( time.series=HRRV[1:nseries],
                     embedding.dim=12, time.lag=1)
hrv2RRVneighs12 <-
  local.findAllNeighbours(hrv2RRVtakens12[-(1:2), ], radius=3.5/16)
save(hrv2RRVneighs12, file="hrv2RRVneighs12.Rdata")
# load(file="hrv2RRVneighs12.RData")
local.recurrencePlotAux(hrv2RRVneighs12, dim=12, radius=3.5/16)
hrv2RRVrqa12 <- showrqa(hrv2RRVtakens12[-(1:2), ], radius=3.5/16, do.hist=FALSE)

```

Output

```

hrv2RRVtakens12[-(1:2), ] n: 1011 Dim: 12
Radius: 0.21875 Recurrence coverage REC: 0.479 log(REC)/log(R): 0.484
Determinism: 0.997 Laminarity: 0.746
DIV: 0.006
Trend: 0 Entropy: 3.803
Diagonal lines max: 156 Mean: 19.62 Mean off main: 19.58
Vertical lines max: 192 Mean: 5.298

```

Dim=12. Time used: 2.723 sec.

Input

```

hrv2RRVtakens16 <- local.buildTakens( time.series=HRRV[1:nseries],
                                         embedding.dim=16, time.lag=1)
hrv2RRVneighs16 <- local.findAllNeighbours(hrv2RRVtakens16[-(1:2), ], radius=4/16)
save(hrv2RRVneighs16, file="hrv2RRVneighs16.Rdata")
# load(file="hrv2RRVneighs16.RData")
local.recurrencePlotAux(hrv2RRVneighs16, dim=16, radius=4/16)
hrv2RRVrqa16 <- showrqa(hrv2RRVtakens16[-(1:2), ], radius=4/16, do.hist=FALSE)

```

Output

```

hrv2RRVtakens16[-(1:2), ] n: 1007 Dim: 16
Radius: 0.25 Recurrence coverage REC: 0.568 log(REC)/log(R): 0.408
Determinism: 0.999 Laminarity: 0.816
DIV: 0.005
Trend: 0 Entropy: 4.186
Diagonal lines max: 221 Mean: 30.105 Mean off main: 30.054
Vertical lines max: 220 Mean: 6.145

```

Dim=16. Time used: 2.887 sec.

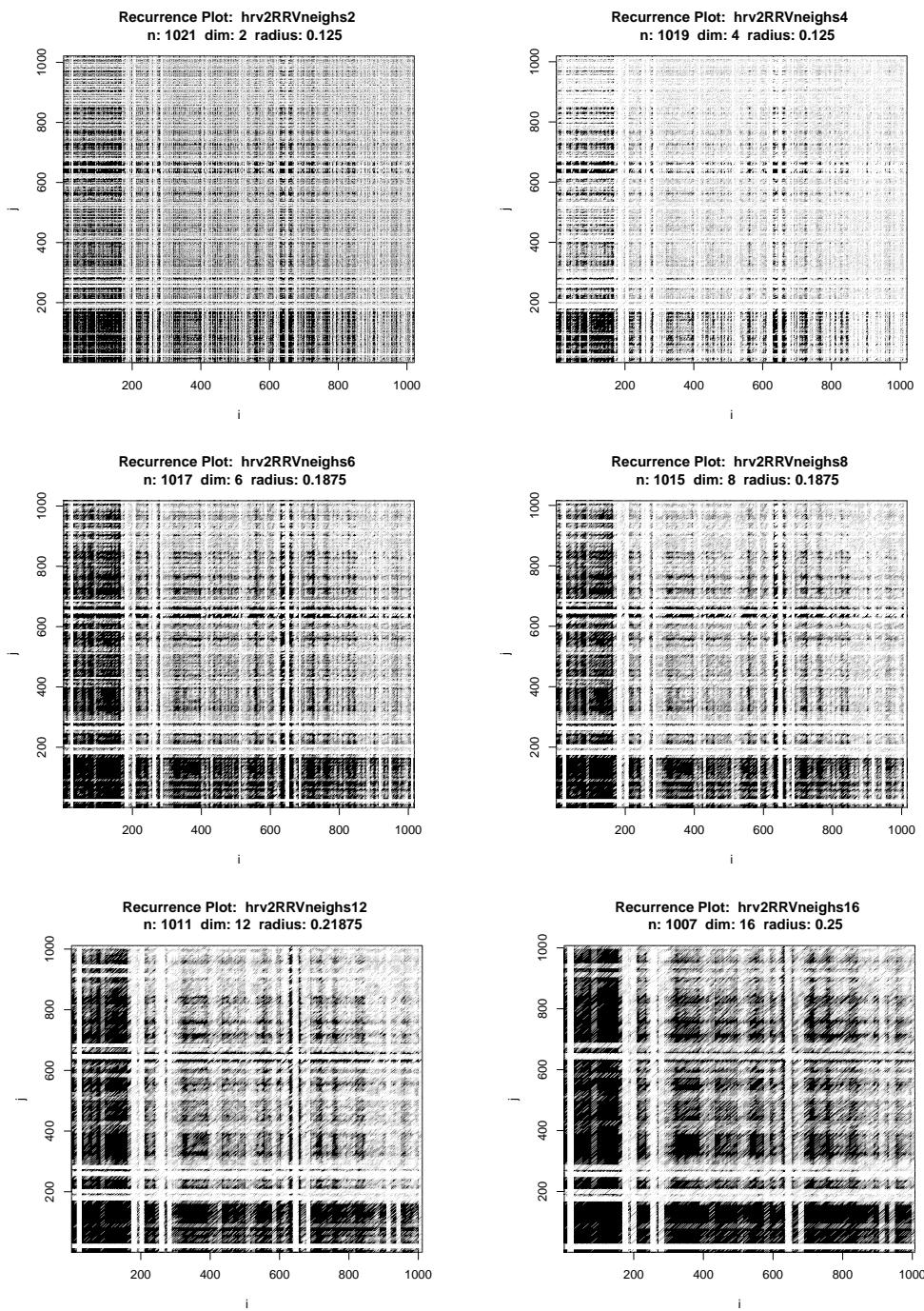


FIGURE 86. Recurrence Plot. Example case: RHRV tutorial example2.beats. Dim=2, 4, 6, 8, 12, 16. Time used: 2.887 sec.

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../sda

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R session info:

Total Sweave time used: 129.804 sec. at Tue Jun 6 16:49:14 2017.

- R version 3.4.0 (2017-04-21), x86_64-apple-darwin15.6.0
- Locale: en_GB.UTF-8/en_GB.UTF-8/en_GB.UTF-8/C/en_GB.UTF-8/en_GB.UTF-8
- Running under: macOS Sierra 10.12.5
- Matrix products: default
- BLAS: /Library/Frameworks/R.framework/Versions/3.4/Resources/lib/libRblas.0.dylib
- LAPACK: /Library/Frameworks/R.framework/Versions/3.4/Resources/lib/libRlapack.dylib
- Base packages: base, datasets, graphics, grDevices, methods, stats, tcltk, utils
- Other packages: leaps 3.0, locfit 1.5-9.1, lomb 1.0, MASS 7.3-47, Matrix 1.2-9, mgcv 1.8-17, nlme 3.1-131, nonlinearTseries 0.2.3, plot3D 1.1, Rcpp 0.12.10, rgl 0.98.1, RHRV 4.2.3, sintro 0.1-6, tkqrplot 0.0-23, TSA 1.01, tsseries 0.10-40, waveslim 1.7.5
- Loaded via a namespace (and not attached): compiler 3.4.0, digest 0.6.12, grid 3.4.0, htmltools 0.3.6, htmlwidgets 0.8, httpuv 1.3.3, jsonlite 1.4, knitr 1.15.1, lattice 0.20-35, magrittr 1.5, mime 0.5, misc3d 0.8-4, quadprog 1.5-5, R6 2.2.0, shiny 1.0.3, tools 3.4.0, xtable 1.8-2, zoo 1.8-0

L^AT_EX information:

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```

Bibliography style: jss

CVS/Svn repository information:

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copied to r-forge
$HeadURL: svn+ssh://gsawitzki@scm.r-forge.r-project.org/svnroot/rhrv/gs/Rnw/recurrence.Rnw $
$Revision: 252 $
$Date: 2017-06-03 18:48:32 +0200 (Sat, 03 Jun 2017) $
$Name:  $
$Author: gsawitzki $
```

E-mail address: gs@statlab.uni-heidelberg.de

GÜNTHER SAWITZKI
 STATLAB HEIDELBERG
 IM NEUENHEIMER FELD 294
 D 69120 HEIDELBERG