Package ‘robfilter’

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Title Robust Time Series Filters

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Imports stats, graphics, utils

Depends R (>= 3.6.0), robustbase, MASS, lattice

Description Implementations for several robust procedures that allow for (online) extraction of the signal of univariate or multivariate time series by applying robust regression techniques to a moving time window are provided. Included are univariate filtering procedures based on repeated-median regression as well as hybrid and trimmed filters derived from it; see Schettlinger et al. (2006) <doi:10.1515/BMT.2006.010>. The adaptive online repeated median by Schettlinger et al. (2010) <doi:10.1002/acs.1105> and the slope comparing adaptive repeated median by Borowski and Fried (2013) <doi:10.1007/s11222-013-9391-7> choose the width of the moving time window adaptively. Multivariate versions are also provided; see Borowski et al. (2009) <doi:10.1080/03610910802514972> for a multivariate online adaptive repeated median and Borowski (2012) <doi:10.17877/DE290R-14393> for a multivariate slope comparing adaptive repeated median. Furthermore, a repeated-median based filter with automatic outlier replacement and shift detection is provided; see Fried (2004) <doi:10.1080/10485250410001656444>.

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`robfilter-package` *Robust Time Series Filters*

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Details

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```

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`adore.filter` *A Robust Adaptive Online Repeated Median Filter for Univariate Time Series*

Description

Procedure for robust online extraction of low frequency components (the *signal*) from a univariate time series by a moving window technique with adaptive window width selection (ADaptive Online REpeated median FILTER).

Usage

```
adore.filter(y,
             p.test=15, minNonNAs=5,
             min.width=10, max.width=200,
             width.search="geometric",
             rtr=2, extrapolate=FALSE,
             calc.qn=FALSE, sign.level=0.1)
```

Arguments

`y`	a numeric vector or (univariate) time series object.
`p.test`	defines the number of most recent Repeated Median residuals within each window used to test the goodness of fit of the online signal level. It can be either a value in (0.25, 0.3, 0.5), meaning that `floor(p.test*width)` residuals are considered for the goodness of fit test, where `width` is the currently used window width, or it can also be a positive integer `>= 5` specifying a fixed number of most recent residuals (default). If the number of residuals considered for the test exceeds `width/2`, the procedure sets it to `floor(width/2)`, if it is smaller than five, the number is set to five.
`minNonNAs`	a positive integer `>= 5` defining the minimum number of non-missing observations within one window which is required for a 'sensible' estimation.

min.width — a positive integer >= 5 specifying the minimal window width.

max.width — a positive integer >= min.width specifying the maximal window width.

width.search — a character string defining the search algorithm used for finding an adequate window width at each point in time.

- "linear" The linear search always results in the largest window width possible and hence yields the smoothest online signal. However, if sudden changes (like level shifts) appear in the signal it requires a lot of computation time and thus, an increased variability of the extracted signal may be observed.
- "binary" The binary search is recommended if it can be expected that the window width needs to be reduced drastically from a large to a very small value at certain times (for example at level shifts or trend changes). However, it may not always result in the largest possible window width.
- "geometric" **(default)** The geometric search is as fast as the binary search but it puts more weight on large window widths. It offers a good compromise between the linear and the binary search (computation time vs. smooth output signal).

rtr — a value in 0, 1, 2 specifying whether a 'restrict to range' rule should be applied.

- rtr=0 The estimated signal level consists of the last fitted value of a Repeated Median regression fit within a time window of adequate width.
- rtr=1 The level estimation is restricted to the range of the observations within each time window.
- rtr=2 **(default)** The level estimation is restricted to the range of the most recent observations (specified by p.test) i.e., to the range of the observations which are used to evaluate the goodness of fit.

extrapolate — a logical indicating whether the level estimations should be extrapolated to the beginning of the time series. The extrapolation consists of all fitted values within the first time window.

calc.qn — a logical indicating whether the Qn scale (Rousseeuw, Croux, 1993) should also be calculated along with the signal level as an estimate of the standard deviation in each window. Here, the Qn command from the robustbase library is applied with the built-in finite sample correction.

sign.level — significance level of the test procedure; must be a value in $(0, 0.5)$.

Details

The adore.filter works by applying Repeated Median (RM) regression (Siegel, 1982) to a moving time window with a length varying between min.width and max.width.

For each point in time, the window width is adapted to the current data situation by a goodness of fit test for the most recent signal level estimation. The test uses the absolute value of the sum of the RM residuals in the subset specified by p.test. The critical value for the test decision corresponds to a slightly modified 0.95-quantile of the distribution of the test statistic and is stored in the data set critvals.

A more detailed description of the filter can be found in Schettlinger, Fried, Gather (2010).

Value

`adore.filter` returns an object of class `adore.filter`. An object of class `adore.filter` is a list containing the following components:

- `level` — a numeric vector containing the signal level extracted by the RM filter with adaptive window width.
- `slope` — a numeric vector containing the corresponding slope within each time window.
- `width` — a numeric vector containing the corresponding window width used for the level and slope estimations.
- `level.list` — a list which contains with as many elements as the length of the input time series. If at time `t`, the window width was not reduced, the entry `level.list[[t]]` simply corresponds to `level[t]`. However, if more than one iteration took place, `level.list[[t]]` is a vector which contains all level estimations which were evaluated until the final estimate `mu[t]` passed the goodness of fit test and was stored.
- `slope.list` — a list containing the slope estimations corresponding to the values in `level.list`.
- `width.list` — a list containing the window widths used for the estimations in `level.list` and `slope.list`.
- `sigma` — a numeric vector containing the corresponding scale within each time window estimated by the robust Qn estimator (only calculated if `calc.qn = TRUE`, else `sigma` does not exist).

In addition, the original input time series is returned as list member `y`, and the settings used for the analysis are returned as the list members `min.width`, `max.width`, `width.search`, `p.test`, `minNonNAs`, `rtr`, `extrapolate`, and `calc.qn`.

Application of the function `plot` to an object of class `aoRM` returns a plot showing the original time series with the filtered output.

Author(s)

Karen Schettlinger

References

Rousseeuw, P. J., Croux, C. (1993) Alternatives to the Median Absolute Deviation, *Journal of the American Statistical Association* **88**, 1273-1283.

Schettlinger, K., Fried, R., Gather, U. (2010) Real Time Signal Processing by Adaptive Repeated Median Filters, *International Journal of Adaptive Control and Signal Processing* **24**(5), 346-362.

Siegel, A.F. (1982) Robust Regression Using Repeated Medians, *Biometrika* **69** (1), 242-244.

See Also

`robreg.filter`, `wrm.filter`, `madore.filter`, `scarm.filter`.

Examples

```
# # # # # # # # # #
# Short and noise-free time series
series <- c(rep(0,30),rep(10,30),seq(10,5,length=20),seq(5,15,length=20))

# Adaptive online signal extraction without & with 'restrict to range' rule
t.without.rtr <- adore.filter(series, rtr=0)
plot(t.without.rtr)
t.with.rtr1 <- adore.filter(series, rtr=1)
lines(t.with.rtr1$level, col="blue")
t.with.rtr2 <- adore.filter(series)
lines(t.with.rtr2$level, col="green3",lty=2)
legend("top",c("Signal with rtr=1","Signal with rtr=2"),col=c("blue","green3"),lty=c(1,2),bty="n")

# # # # # # # # # #
# Short and noise-free time series + 1 outlier
ol.series <- series
ol.series[63] <- 3

# Adaptive online signal extraction without & with 'restrict to range' rule
t.without.rtr <- adore.filter(ol.series, rtr=0)
plot(t.without.rtr)
t.with.rtr1 <- adore.filter(ol.series, rtr=1)
lines(t.with.rtr1$level, col="blue")
t.with.rtr2 <- adore.filter(ol.series)
lines(t.with.rtr2$level, col="green3",lty=2)
legend("top",c("Signal with rtr=1","Signal with rtr=2"),col=c("blue","green3"),lty=c(1,2),bty="n")

# # # # # # # # # #
# Noisy time series with level shifts, trend changes and shifts in the scale of the error term
true.signal  <- c(rep(0,150),rep(10,150),seq(10,5,length=100),seq(5,15,length=100))
series2      <- true.signal + c(rnorm(250,sd=1), rnorm(200,sd=3), rnorm(50,sd=1))

# Adaptive online signal extraction with additional Qn scale estimation
s2 <- adore.filter(series2, calc.qn=TRUE)
par(mfrow=c(3,1))
plot(s2)
plot(s2$sigma,type="l",main="Corresponding Qn Scale Estimation",ylab="sigma",xlab="time")
lines(c(rep(1,250),rep(3,200),rep(1,150)),col="grey")
legend("topleft",c("True scale","Qn"),lty=c(1,1),col=c("grey","black"),bty="n")
plot(s2$width,type="l",main="Corresponding Window Width",ylab="width",xlab="time")
```

`const` *Correction factors to achieve unbiasedness of the Qn scale estimator*

Description

This matrix contains correction factors for the univariate Qn scale estimator (Rousseeuw, Croux, 1993) to achieve unbiasedness under Gaussian noise. The `madore.filter` estimates the local error covariance matrix by the orthogonalized Gnanadesikan-Kettenring estimator (Gnanadesikan, Kettenring, 1972, Maronna, Zamar, 2002) which is based on the Qn scale estimator.

Usage

```
const
```

Format

A (96x2)-matrix containing the correction factors for the univariate Qn scale estimator for the samples sizes $n = 10, 11, ..., 100, 200, 300, 400, 500, 1000$.

Source

The correction factors have been obtained by simulations.

References

Gnanadesikan, R., Kettenring, J.R. (1972) Robust Estimates, Residuals, and Outlier Detection with Multiresponse Data, *Biometrics* **28**, 81-124.

Maronna, R.A., Zamar, R.H. (2002) Robust Estimates of Location and Dispersion for High-Dimensional Datasets, *Technometrics* **44**, 307-317.

Rousseeuw, P.J., Croux, C. (1993) Alternatives to the Median Absolute Deviation, *Journal of the American Statistical Association* **88**, 1273-1283.

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const.Q — *Correction factors to achieve unbiasedness of the regression-free Q scale estimator*

Description

Correction factors for the regression-free Q scale estimator (Rousseeuw and Hubert, 1996, Gelper et al., 2009) to achieve unbiasedness under Gaussian noise; required by the function `scarm.filter`.

Usage

```
data(const.Q)
```

Format

The format is: num [1:151] NA NA NA NA 2.17 ...

Source

The correction factors have been obtained by simulations.

References

Rousseeuw, P. and Hubert, M. (1996) Regression-free and robust estimation of scale for bivariate data, *Computational Statistics and Data Analysis*, **21**(1), 67-85.

Gelper, S., Schettlinger, K., Croux, C., and Gather, U. (2009) Robust online scale estimation in time series: A model-free approach, *Journal of Statistical Planning and Inference*, **139**(2), 335-349.

`critvals` *Critical Values for the RM Goodness of Fit Test*

Description

This matrix contains critical values for the goodness of fit test for the last fitted value of a Repeated Median regression fit to a sample of size `n`. The critical values are based on the 0.95-quantiles of the distribution of a test statistic corresponding to the absolute value of the sum of a subset of residual signs. The critical value for a test based on the last `nI` out of `n` observations corresponds to `critvals[n,nI]`.

Usage

```
critvals
```

Format

A (600x61)-matrix containing 30550 observations.

Source

Simulation.

References

Schettlinger, K., Fried, R., Gather, U. (2008) Real Time Signal Processing by Adaptive Repeated Median Filters, *International Journal of Adaptive Control and Signal Processing*, submitted.

Siegel, A.F. (1982) Robust Regression Using Repeated Medians, *Biometrika* **69** (1), 242-244.

dfs *Degrees of freedom for the SCARM test statistic.*

Description

This matrix contains degrees of freedom for the t-distributed SCARM test statistic; required by the function `scarm.filter`.

Usage

```
data(dfs)
```

Format

A data frame with 20 observations on the following 20 variables.

- `X5` a numeric vector
- `X10` a numeric vector
- `X15` a numeric vector
- `X20` a numeric vector
- `X25` a numeric vector
- `X30` a numeric vector
- `X35` a numeric vector
- `X40` a numeric vector
- `X45` a numeric vector
- `X50` a numeric vector
- `X55` a numeric vector
- `X60` a numeric vector
- `X65` a numeric vector
- `X70` a numeric vector
- `X75` a numeric vector
- `X80` a numeric vector
- `X85` a numeric vector
- `X90` a numeric vector
- `X95` a numeric vector
- `X100` a numeric vector

Details

The SCARM test from the function `scarm.filter` is based on the difference of Repeated Median slopes computed in a left-hand and right-hand window. The distribution of the SCARM test statistic is approximated by a t-distribution where the degrees of freedom depend on the width of the left- and right-hand window. This matrix delivers suitable degrees of freedom, obtained by simulations.

Source

The degrees of freedom have been obtained by simulations.

References

Borowski, M. and Fried, R. (2011) Robust moving window regression for online signal extraction from non-stationary time series: online window width adaption by testing for signal changes, *submitted*.

`dr.filter` *Deepest Regression (DR) filter*

Description

This function extracts signals from time series by means of Deepest regression in a moving time window.

Usage

```
dr.filter(y, width, online = FALSE, extrapolate = TRUE)
```

Arguments

`y`	a numeric vector or (univariate) time series object.
`width`	a positive integer defining the window width used for fitting. If `online=FALSE` (see below) this needs to be an odd integer.
`online`	a logical indicating whether the current level estimate is evaluated at the most recent time within each time window (`TRUE`) or centred within each window (`FALSE`). Setting `online=FALSE` requires the `width` to be odd. Default is `online=FALSE`.
`extrapolate`	a logical indicating whether the level estimations should be extrapolated to the edges of the time series. If `online=FALSE` the extrapolation consists of the fitted values within the first half of the first window and the last half of the last window; if `online=TRUE` the extrapolation consists of the fitted values within the first time window.

Details

`dr.filter` is suitable for extracting low frequency components (the *signal*) from a time series which may be contaminated with outliers and can contain level shifts. For this, robust Deepest Regression is applied to a moving window, and the signal level is estimated by the fitted value either at the end of each time window for online signal extraction without time delay (`online=TRUE`) or in the centre of each time window (`online=FALSE`).

Value

dr.filter returns an object of class robreg.filter. An object of class robreg.filter is a list containing the following components:

level	a data frame containing the extracted signal level.
slope	a data frame containing the corresponding slope within each time window.

In addition, the original input time series is returned as list member y, and the settings used for the analysis are returned as the list members width, online and extrapolate.

Application of the function plot to an object of class robreg.filter returns a plot showing the original time series with the filtered output.

Author(s)

Roland Fried, Karen Schettlinger and Matthias Borowski

References

Davies, P.L., Fried, R., Gather, U. (2004) Robust Signal Extraction for On-Line Monitoring Data, *Journal of Statistical Planning and Inference* **122**, 65-78.

Gather, U., Schettlinger, K., Fried, R. (2006) Online Signal Extraction by Robust Linear Regression, *Computational Statistics* **21**(1), 33-51.

Schettlinger, K., Fried, R., Gather, U. (2006) Robust Filters for Intensive Care Monitoring: Beyond the Running Median, *Biomedizinische Technik* **51**(2), 49-56.

See Also

robreg.filter

Examples

```
# Generate random time series:
y <- cumsum(runif(500)) - .5*(1:500)
# Add jumps:
y[200:500] <- y[200:500] + 5
y[400:500] <- y[400:500] - 7
# Add noise:
n <- sample(1:500, 30)
y[n] <- y[n] + rnorm(30)

# Online filtering with DR filter:
y.rr <- dr.filter(y,width=41,online=TRUE)
plot(y.rr)
```

dw.filter *Robust Double Window Filtering Methods for Univariate Time Series*

Description

Procedures for robust (online) extraction of low frequency components (the *signal*) from a univariate time series based on a moving window technique using two nested time windows in each step.

Usage

```
dw.filter(y, outer.width, inner.width, method = "all",
            scale = "MAD", d = 2,
            minNonNAs = 5, online = FALSE, extrapolate = TRUE)
```

Arguments

`y` a numeric vector or (univariate) time series object.

`outer.width` a positive integer specifying the window width of the outer window used for determining the final estimate.
If `online=FALSE` (see below) this needs to be an odd integer.

`inner.width` a positive integer (not larger than `outer.width`) specifying the window width of the inner window used for determining the initial estimate and trimming features.
If `online=FALSE` (see below) this needs to be an odd integer.

`method` a (vector of) character string(s) containing the method(s) to be used for the estimation of the signal level.
It is possible to specify any combination of `"MED"`, `"RM"`, `"MTM"`, `"TRM"`, `"MRM"`, `"DWRM"`, `"DWMTM"`, `"DWTRM"`, `"DWMRM"` and `"all"` (for all of the above). Default is `method="all"`. For a detailed description see the section 'Methods' below.

`scale` a character string specifying the method to be used for robust estimation of the local variability (within one time window). Possible values are:

- `"MAD"` Median absolute deviation about the median (default)
- `"QN"` Rousseeuw's and Croux' (1993) Q_n scale estimator
- `"SN"` Rousseeuw's and Croux' (1993) S_n scale estimator

`d` a positive integer defining factor the current scale estimate is multiplied with for determining the trimming boundaries for outlier detection.
Observations deviating more than $d \cdot \hat{\sigma}_t$ from the current level approximation $\hat{\mu}_t$ are replaced by $\hat{\mu}_t$ where $\hat{\sigma}_t$ denotes the current scale estimate. Default is `d = 2` meaning a 2σ rule for outlier detection.

`minNonNAs` a positive integer defining the minimum number of non-missing observations within each window which is required for a 'sensible' estimation. Default: if windows contain less than `minNonNAs = 5` observations `NA`s are returned.

online — a logical indicating whether the current level and scale estimates are evaluated at the most recent time within each (inner and outer) window (`TRUE`) or centred within the windows (`FALSE`). Setting `online=FALSE` requires odd `inner.width` and `outer.width`. Default is `online=FALSE`.

extrapolate — a logical indicating whether the level estimations should be extrapolated to the edges of the time series.
If `online=FALSE` the extrapolation consists of the fitted values within the first half of the first window and the last half of the last window; if `online=TRUE` the extrapolation consists of the all fitted values within the first time window.

Details

`dw.filter` is suitable for extracting low frequency components (the *signal*) from a time series which may be contaminated with outliers and can contain level shifts. For this, moving window techniques are applied.

A short inner window of length `inner.width` is used in each step for calculating an initial level estimate (by using either the median or a robust regression fit) and a robust estimate of the local standard deviation. Observations deviating strongly from this initial fit are trimmed from an outer time window of length `outer.width`, and the signal level is estimated from the remaining observations (by using either a location or regression estimator). Values specified in `method` determine which combination of estimation methods should be applied to the inner and outer window (see section 'Methods' below).

The applied `method` should be chosen based on an a-priori guess of the underlying signal and the data quality: Location based method (`MED` / `MTM`) are recommended in case of a locally (piecewise) constant signal, regression based approaches (`RM` / `DWRM` / `TRM` / `MRM`) in case of locally linear, monotone trends.

Since no big differences have been reported between `TRM` and `MRM`, the quicker and somewhat more efficient `TRM` option might be preferred. `DWRM` is the quickest of all regression based methods and performs better than the ordinary `RM` at shifts, but it is the least robust and least efficient method.

If location based methods are used, the `inner.width` should be chosen at least twice the length of expected patches of subsequent outliers in the time series; if regression based methods are used, the `inner.width` should be at least three times that length, otherwise outlier patches can influence the estimations strongly. To increase the efficiency of the final estimates, `outer.width` can then be chosen rather large - provided that it is smaller than the time between subsequent level shifts.

For robust scale estimation, `MAD` is the classical choice; `SN` is a somewhat more efficient and almost equally robust alternative, while `QN` is much more efficient if the window widths are not too small, and it performs very well at the occurrence of level shifts.

The factor `d`, specifying the trimming boundaries as a multiple of the estimated scale, can be chosen similarly to classical rules for detecting unusual observations in a Gaussian sample. Choosing `d=3` instead of `d=2` increases efficiency, but decreases robustness; `d=2.5` might be seen as a compromise.

Value

`dw.filter` returns an object of class `dw.filter`. An object of class `dw.filter` is a list containing the following components:

level — a data frame containing the corresponding signal level extracted by the filter(s) specified in method.

slope — a data frame containing the corresponding slope within each time window.

sigma — a data frame containing inner.loc.sigma, inner.reg.sigma, outer.loc.sigma and outer.reg.sigma, the scale estimated from the observations (loc) or the residuals from the Repeated Median regression (reg) within the inner window of length inner.width or the outer window of length outer.width, respectively.
MTM uses outer.loc.sigma for trimming outliers, MRM and TRM use outer.reg.sigma for trimming outliers,
DWMTM uses inner.loc.sigma for trimming outliers, DWMRM and DWTRM use inner.reg.sigma for trimming outliers;
MED, RM and RM require no scale estimation.
The function only returns values for inner.loc.sigma, inner.reg.sigma, outer.loc.sigma or outer.reg.sigma if any specified method requires their estimation; otherwise NAs are returned.

In addition, the original input time series is returned as list member y, and the settings used for the analysis are returned as the list members outer.width, inner.width, method, scale, d, minNonNAs, online and extrapolate.

Application of the function plot to an object of class dw.filter returns a plot showing the original time series with the filtered output.

Methods

The following methods are available as method for signal extraction, whereby the prefix DW denotes the fact that different window widths are used in the first and second step of the calculations within one window (i.e. inner.width<outer.width) while for the methods MED, RM, MTM, TRM and MRM the first and second step take place in a window of fixed length outer.width.

MED ordinary running median filter.
The simple median is applied to the observations within a moving time window of length outer.width.

RM ordinary repeated median filter.
Repeated median regression is applied to the observations within a moving time window of length outer.width.

MTM, DWMTM modified trimmed mean filters.
In a first step the median is applied to (MTM): the whole window with outer.width or (DWMTM): the inner window with inner.width; in a second step the mean is applied to the (trimmed) observations in the whole window (with outer.width).

TRM, DWTRM trimmed repeated median filters.
In a first step repeated median regression is applied to (TRM): the whole window with outer.width or (DWTRM): the inner window with inner.width; in a second step least squares regression is applied to the (trimmed) observations in the whole window (with outer.width).

MRM, DWMRM modified repeated median filters.
In a first step repeated median regression is applied to (MRM): the whole window with outer.width or (DWMRM): the inner window with inner.width; in a second step another repeated median regression is applied to the (trimmed) observations in the whole window (with outer.width).

DWRM double window repeated median filter.
In a first step repeated median regression is applied to the inner window with inner.width to determine the trend (slope); in a second step the median is applied to the trend corrected observations in the whole window with outer.width (without trimming).

Note

Missing values are treated by omitting them and thus by reducing the corresponding window width. MED, RM, MTM, TRM and MRM require at least minNonNAs non-missing observations in each outer window; DWRM, DWMTM, DWTRM and DWMRM require at least minNonNAs non-missing observations in each inner window. Otherwise NAs are returned for level, slope and sigma.

Author(s)

Roland Fried and Karen Schettlinger

References

Bernholt, T., Fried, R., Gather, U., Wegener, I. (2006) Modified Repeated Median Filters, *Statistics and Computing* **16**, 177-192.
(earlier version: http://hdl.handle.net/2003/5298)

Schettlinger, K., Fried, R., Gather, U. (2006) Robust Filters for Intensive Care Monitoring: Beyond the Running Median, *Biomedizinische Technik* **51**(2), 49-56.

See Also

robreg.filter, robust.filter, hybrid.filter, wrm.filter.

Examples

```
## Not run:
# Generate random time series:
y <- cumsum(runif(500)) - .5*(1:500)
# Add jumps:
y[200:500] <- y[200:500] + 5
y[400:500] <- y[400:500] - 7
# Add noise:
n <- sample(1:500, 30)
y[n] <- y[n] + rnorm(30)

# Filtering with all methods:
y.dw <- dw.filter(y, outer.width=31, inner.width=11, method="all")
# Plot:
plot(y.dw)

# Filtering with trimmed RM and double window TRM only:
y2.dw <- dw.filter(y, outer.width=31, inner.width=11, method=c("TRM","DWTRM"))
plot(y2.dw)

## End(Not run)
```

`hybrid.filter` *Robust Hybrid Filtering Methods for Univariate Time Series*

Description

Procedures for robust extraction of low frequency components (the *signal*) from a univariate time series based on a moving window technique using the median of several one-sided half-window estimates (subfilters) in each step.

Usage

```
hybrid.filter(y, width, method = "all", minNonNAs=3, extrapolate = TRUE)
```

Arguments

`y`	a numeric vector or (univariate) time series object.
`width`	an odd positive integer (≥ 3) defining the window width used for fitting.
`method`	a (vector of) character string(s) containing the method(s) to be used for the estimation of the signal level. It is possible to specify any combination of `"MED"`, `"RM"`, `"MEAN"`, `FMH`, `"PFMH"`, `"CFMH"`, `"MH"`, `"PRMH"`, `"CRMH"`, `"MMH"`, `"PRMMH"`, `"CRMMH"`, and `"all"` (for all of the above). Default is `method="all"`. For a detailed description see the section 'Methods' below.
`minNonNAs`	a positive integer defining the minimum number of non-missing observations within each window (half) which is required for a 'sensible' estimation. Default: if a window (half) contains less than `minNonNAs = 3` observations an `NA` is returned (for that subfilter).
`extrapolate`	a logical indicating whether the level estimations should be extrapolated to the edges of the time series. The extrapolation extends the first estimated value to the first time in the first window and the last estimated value to the last time in the last time window. Default is `extrapolate=TRUE`.

Details

`hybrid.filter` is suitable for extracting low frequency components (the *signal*) from a time series which may be contaminated with outliers and can contain level shifts or local extremes. For this, moving window techniques are applied.

Within each time window several subfilters are applied to half-windows (left and right of the centre); the final signal level in the centre of the time window is then estimated by the median of the subfilter outputs.

For the subfilters, both, location-based and regression-based method are available, the former applying means or medians and the idea of a locally constant signal value, the latter using ordinary least squares (LS) regression or Siegel's (1982) repeated median (RM) and the idea of an underlying locally linear trend.

The methods should be chosen based on an a-priori guess of the underlying signal and the data quality. Location based methods (`MED`, `MEAN`, `FMH`, `MH`, `MMH`) are recommended in case of a locally (piecewise) constant signal. Regression based and predictive approaches (`RM`, `PFMH`, `PRMH`, `PRMMH`) in case of locally linear monotone trends. The combined filters (`CFMH`, `CRMH`, `CRMMH`) can be seen as a compromise, but are computationally somewhat more expensive and may be inferior to the predictive filters during steep trends.

The approaches based on the median and RM are robust alternatives to the (in Gaussian samples) more efficient mean and least squares methods. The hybrid filters preserve shifts and local extremes much better than `MED`, `MEAN` or `RM` for the price of decreased robustness and / or Gaussian efficiency.

Value

`hybrid.filter` returns an object of class `hybrid.filter`. An object of class `hybrid.filter` is a list containing the following components:

`level` a data frame containing the signal level extracted by the filter(s) specified in `method`.

`slope` a data frame (possibly) containing `RM`, `RM.left`, `RM.right`, `LS.left` and `LS.right`: the slope estimated by Repeated Median regression in the whole window (for `method="RM"`) or in the left and right window half (for any `method` in `"PRMH"`, `"CRMH"`, `"PRMMH"` and `"CRMMH"`) or the least squares slope estimated from the left and right window half (for any `method` in `"PRFMH"` or `"CFMH"`).
Only those slopes are returned which are required by the filters specified in `method`. If only location-based filters are applied (i.e. `"MED"`, `"MEAN"`, `"FMH"`, `"MH"` and /or `"MMH"`) `NULL` is returned for the `slope`.

In addition, the original input time series is returned as list member `y`, and the settings used for the analysis are returned as the list members `width`, `method` and `extrapolate`.

Application of the function `plot` to an object of class `hybrid.filter` returns a plot showing the original time series with the filtered output.

Methods

The following methods are available as `method` for signal extraction.

Filters applying only *one* location or regression estimate to the whole window of length `width` and taking the location (in the centre of the time window) as final signal level estimate:

`MED` ordinary running median filter.

`MEAN` ordinary moving average filter.

`RM` ordinary repeated median filter.
Applies repeated median regression to each time window.

Filters applying several subfilters within one window, taking the median of the values listed below as the final signal level estimate:

`FMH` FIR median hybrid filter.
Uses half-window averages and the central observation.

`PFMH` predictive `FMH` filter.
Uses half-window least squares regression and the central observation.

CFMH combined FMH filter.
: Uses half-window averages, half-window least squares regression, and the central observation.

MH median hybrid filter.
: Uses half-window medians and the central observation.

PRMH predictive repeated median hybrid filter.
: Uses half-window repeated median regression and the central observation.

CRMH combined repeated median hybrid filter.
: Uses half-window medians, half-window repeated median regression, and the central observation.

MMH median/median hybrid filter.
: Uses half-window medians and the median of all observations in the window.

PRMMH predictive repeated median/median filter.
: Uses half-window repeated median regression and the median of all observations in the window.

CRMMH combined repeated median/median filter.
: Uses half-window medians, half-window repeated median regression, and the median of all observations in the window.

Note

Missing values are treated by omitting them and thus by reducing the corresponding window width. The hybrid.filter function only offers filters for signal extraction delayed by (width+1)/2 time units, in contrast to other filters available from the robfilter package which also offer online time series analysis without time delay.

Author(s)

Roland Fried and Karen Schettlinger

References

Fried, R., Bernholt, T., Gather, U. (2006) Repeated Median and Hybrid Filters, *Computational Statistics & Data Analysis* **50**, 2313-2338.
(earlier version: http://hdl.handle.net/2003/4866)

Schettlinger, K., Fried, R., Gather, U. (2006) Robust Filters for Intensive Care Monitoring: Beyond the Running Median, *Biomedizinische Technik* **51**(2), 49-56.

See Also

robreg.filter, robust.filter, dw.filter, wrm.filter.

Examples

```
# Generate random time series:
y <- cumsum(runif(500)) - .5*(1:500)
# Add jumps:
y[200:500] <- y[200:500] + 5
y[400:500] <- y[400:500] - 7
```

```
# Add noise:
n <- sample(1:500, 30)
y[n] <- y[n] + rnorm(30)
# Filtering with all methods:
y.hy <- hybrid.filter(y, width=31)
# Plot:
plot(y.hy)

# Filtering with running median and PRMH only:
y2.hy <- hybrid.filter(y, width=31, method=c("MED","PRMH"))
plot(y2.hy)
```

---

lms.filter *Least Median of Squares (LMS) filter*

Description

This function extracts signals from time series by means of Least Median of Squares regression in a moving time window.

Usage

```
lms.filter(y, width, online = FALSE, extrapolate = TRUE)
```

Arguments

y	a numeric vector or (univariate) time series object.
width	a positive integer defining the window width used for fitting. If `online=FALSE` (see below) this needs to be an odd integer.
online	a logical indicating whether the current level estimate is evaluated at the most recent time within each time window (`TRUE`) or centred within each window (`FALSE`). Setting `online=FALSE` requires the `width` to be odd. Default is `online=FALSE`.
extrapolate	a logical indicating whether the level estimations should be extrapolated to the edges of the time series. If `online=FALSE` the extrapolation consists of the fitted values within the first half of the first window and the last half of the last window; if `online=TRUE` the extrapolation consists of the fitted values within the first time window.

Details

`lms.filter` is suitable for extracting low frequency components (the *signal*) from a time series which may be contaminated with outliers and can contain level shifts. For this, robust Least Median of Squares regression is applied to a moving window, and the signal level is estimated by the fitted value either at the end of each time window for online signal extraction without time delay (`online=TRUE`) or in the centre of each time window (`online=FALSE`).

Value

`lms.filter` returns an object of class `robreg.filter`. An object of class `robreg.filter` is a list containing the following components:

`level`	a data frame containing the extracted signal level.
`slope`	a data frame containing the corresponding slope within each time window.

In addition, the original input time series is returned as list member `y`, and the settings used for the analysis are returned as the list members `width`, `online` and `extrapolate`.

Application of the function `plot` to an object of class `robreg.filter` returns a plot showing the original time series with the filtered output.

Author(s)

Roland Fried, Karen Schettlinger and Matthias Borowski

References

Davies, P.L., Fried, R., Gather, U. (2004) Robust Signal Extraction for On-Line Monitoring Data, *Journal of Statistical Planning and Inference* **122**, 65-78.

Gather, U., Schettlinger, K., Fried, R. (2006) Online Signal Extraction by Robust Linear Regression, *Computational Statistics* **21**(1), 33-51.

Schettlinger, K., Fried, R., Gather, U. (2006) Robust Filters for Intensive Care Monitoring: Beyond the Running Median, *Biomedizinische Technik* **51**(2), 49-56.

See Also

`robreg.filter`

Examples

```
# Generate random time series:
y <- cumsum(runif(500)) - .5*(1:500)
# Add jumps:
y[200:500] <- y[200:500] + 5
y[400:500] <- y[400:500] - 7
# Add noise:
n <- sample(1:500, 30)
y[n] <- y[n] + rnorm(30)

# Online filtering with LMS filter:
y.rr <- lms.filter(y,width=41,online=FALSE)
plot(y.rr)
```

lqd.filter *Least Quartile Difference filter*

Description

This function extracts signals from time series by means of Least Quartile Difference regression in a moving time window.

Usage

```
lqd.filter(y, width, online = FALSE, extrapolate = TRUE)
```

Arguments

y	a numeric vector or (univariate) time series object.
width	a positive integer defining the window width used for fitting. If online=FALSE (see below) this needs to be an odd integer.
online	a logical indicating whether the current level estimate is evaluated at the most recent time within each time window (TRUE) or centred within each window (FALSE). Setting online=FALSE requires the width to be odd. Default is online=FALSE.
extrapolate	a logical indicating whether the level estimations should be extrapolated to the edges of the time series. If online=FALSE the extrapolation consists of the fitted values within the first half of the first window and the last half of the last window; if online=TRUE the extrapolation consists of the fitted values within the first time window.

Details

lqd.filter is suitable for extracting low frequency components (the *signal*) from a time series which may be contaminated with outliers and can contain level shifts. For this, robust Least Quartile Difference regression is applied to a moving window, and the signal level is estimated by the fitted value either at the end of each time window for online signal extraction without time delay (online=TRUE) or in the centre of each time window (online=FALSE).

Value

lqd.filter returns an object of class robreg.filter. An object of class robreg.filter is a list containing the following components:

level	a data frame containing the extracted signal level.
slope	a data frame containing the corresponding slope within each time window.

In addition, the original input time series is returned as list member y, and the settings used for the analysis are returned as the list members width, online and extrapolate.

Application of the function plot to an object of class robreg.filter returns a plot showing the original time series with the filtered output.

Author(s)

Roland Fried, Karen Schettlinger and Matthias Borowski

References

Davies, P.L., Fried, R., Gather, U. (2004) Robust Signal Extraction for On-Line Monitoring Data, *Journal of Statistical Planning and Inference* **122**, 65-78.

Gather, U., Schettlinger, K., Fried, R. (2006) Online Signal Extraction by Robust Linear Regression, *Computational Statistics* **21**(1), 33-51.

Schettlinger, K., Fried, R., Gather, U. (2006) Robust Filters for Intensive Care Monitoring: Beyond the Running Median, *Biomedizinische Technik* **51**(2), 49-56.

See Also

robreg.filter

Examples

```
# Generate random time series:
y <- cumsum(runif(500)) - .5*(1:500)
# Add jumps:
y[200:500] <- y[200:500] + 5
y[400:500] <- y[400:500] - 7
# Add noise:
n <- sample(1:500, 30)
y[n] <- y[n] + rnorm(30)

# Online filtering with LQD filter:
y.rr <- lqd.filter(y,width=41,online=FALSE)
plot(y.rr)
```

---

lts.filter *Least Trimmed Squares (LTS) filter*

Description

This function extracts signals from time series by means of Least Trimmed Squares regression in a moving time window.

Usage

```
lts.filter(y, width, h = floor(width/2) + 1, online = FALSE, extrapolate = TRUE)
```

Arguments

- `y` a numeric vector or (univariate) time series object.
- `width` a positive integer defining the window width used for fitting. If `online=FALSE` (see below) this needs to be an odd integer.
- `h` a positive integer defining the trimming quantile.
- `online` a logical indicating whether the current level estimate is evaluated at the most recent time within each time window (`TRUE`) or centred within each window (`FALSE`). Setting `online=FALSE` requires the `width` to be odd. Default is `online=FALSE`.
- `extrapolate` a logical indicating whether the level estimations should be extrapolated to the edges of the time series.
  If `online=FALSE` the extrapolation consists of the fitted values within the first half of the first window and the last half of the last window; if `online=TRUE` the extrapolation consists of the fitted values within the first time window.

Details

`lts.filter` is suitable for extracting low frequency components (the *signal*) from a time series which may be contaminated with outliers and can contain level shifts. For this, robust Least Trimmed Squares regression is applied to a moving window, and the signal level is estimated by the fitted value either at the end of each time window for online signal extraction without time delay (`online=TRUE`) or in the centre of each time window (`online=FALSE`).

Value

`lts.filter` returns an object of class `robreg.filter`. An object of class `robreg.filter` is a list containing the following components:

- `level` a data frame containing the extracted signal level.
- `slope` a data frame containing the corresponding slope within each time window.

In addition, the original input time series is returned as list member `y`, and the settings used for the analysis are returned as the list members `width`, `online` and `extrapolate`.

Application of the function `plot` to an object of class `robreg.filter` returns a plot showing the original time series with the filtered output.

Author(s)

Roland Fried, Karen Schettlinger and Matthias Borowski

References

Davies, P.L., Fried, R., Gather, U. (2004) Robust Signal Extraction for On-Line Monitoring Data, *Journal of Statistical Planning and Inference* **122**, 65-78.

Gather, U., Schettlinger, K., Fried, R. (2006) Online Signal Extraction by Robust Linear Regression, *Computational Statistics* **21**(1), 33-51.

Schettlinger, K., Fried, R., Gather, U. (2006) Robust Filters for Intensive Care Monitoring: Beyond the Running Median, *Biomedizinische Technik* **51**(2), 49-56.

See Also

robreg.filter

Examples

```
# Generate random time series:
y <- cumsum(runif(500)) - .5*(1:500)
# Add jumps:
y[200:500] <- y[200:500] + 5
y[400:500] <- y[400:500] - 7
# Add noise:
n <- sample(1:500, 30)
y[n] <- y[n] + rnorm(30)

# Online filtering with LTS filter:
y.rr <- lts.filter(y,width=41,online=FALSE)
plot(y.rr)
```

---

madore.filter — *A multivariate adaptive online repeated median filter*

Description

Procedure for robust signal extraction from a multivariate time series by a moving window technique with adaptive window width selection (*m*ultivariate *ad*aptive *o*nline *re*peated median filter). The window width adaption is based on the univariate `adore.filter`.

Usage

```
madore.filter(Y, byrow=FALSE,
              min.width=10, max.width=200,
              test.sample.size=min.width/2,
              width.search="geometric",
              rtr.size=min.width, sign.level=0.1,
              NA.sample.size=min.width, minNonNAs=min.width/2)
```

Arguments

`Y`	a numeric matrix or (multivariate) time series object.
`byrow`	logical. If `FALSE` (the default), the filtering is done by columns, otherwise the filtering is done by rows.
`min.width`	a positive integer ≥ 10 specifying the minimal width of the moving time window.

`max.width` a positive integer $\geq$ `min.width` specifying the maximal width of the moving time window. If `min.width` = `max.width`, the window width is fixed.

`test.sample.size` a positive integer in [5, `min.width`] defining a test window of the rightmost `test.sample.size` time points within the current time window. The *Repeated Median* (RM) regression residuals within the test window are used for a goodness of fit test (see `adore.filter`) for finding an adequate window width. For more details about the test, see Schettlinger, Fried, Gather (2010).

`width.search` a character string defining the search algorithm used for finding an adequate window width at each point in time.

- `"linear"` The linear search always results in the largest window width possible and hence yields the smoothest online signal. However, if sudden changes (like level shifts) appear in the signal it requires a lot of computation time and thus, an increased variability of the extracted signal may be observed.
- `"binary"` The binary search is recommended if it can be expected that the window width needs to be reduced drastically from a large to a very small value at certain times (for example at level shifts or trend changes). However, it may not always result in the largest possible window width.
- `"geometric"` **(default)** The geometric search is as fast as the binary search but it puts more weight on large window widths. It offers a good compromise between the linear and the binary search (computation time vs. smooth output signal).

`rtr.size` a non-negative integer specifying the size of a subset of the most recent observations within each window. The signal estimation is restricted to the range of the observations within this subset.

`sign.level` the level of significance for the goodness of fit test (see `adore.filter`) for finding an adequate window width. For more details about the test, see Schettlinger, Fried, Gather (2010).

`NA.sample.size` a positive integer in [10, `min.width`] specifying the size of a subset of the most recent observations within each window. See `minNonNAs`.

`minNonNAs` a positive integer in [5, `NA.sample.size`]. If a variable does not offer at least `minNonNAs` non-missing observations within the subset specified by `NA.sample.size`, the signal is not estimated for this variable at this time point t.

Details

The `madore.filter` is based on *Repeated Median* regression (Siegel, 1982) in moving time windows and serves for separating signals from noise and outliers in multivariate time series. At each time point t the test procedure of the *adaptive online Repeated Median* filter (Schettlinger, Fried, Gather, 2010) is used to determine an appropriate window width $n(t)$ in [`min.width`, `max.width`]. Then the signal vector at time t is estimated within the time window $(t - n(t) + 1, \dots, t)$ by a slight modification of the multivariate *Trimmed Repeated Median-Least Squares* regression (Lanius, Gather, 2010). A more detailed description of the `madore.filter` can be found in Borowski, Schettlinger, Gather (2009).

Value

madore.filter returns an object of class madore.filter. An object of class madore.filter is a list containing the following components:

signals	a matrix containing the estimated signal vectors at each time point t.
widths	a matrix containing the individual window widths of each variable at each time point t.
overall.width	a vector containing the overall window widths at each time point t.

In addition, the original input data is returned as list member Y, and the settings used for the analysis are returned as the list members byrow, min.width, max.width, start.width, test.sample.size, width.search, rtr.size, extr.delay, NA.sample.size, and minNonNAs. Application of the function plot to an object of class madore.filter returns a plot showing the original multivariate time series with the filtered output.

Author(s)

Matthias Borowski

References

Borowski, M., Schettlinger, K., Gather, U. (2009) Multivariate Real Time Signal Extraction by a Robust Adaptive Regression Filter, *Communications in Statistics - Simulation and Computation* **38**, 426-440.

Lanius, V., Gather, U. (2010) Robust Online Signal Extraction from Multivariate Time Series, *Computational Statistics and Data Analysis* **54**(4), 966-975.

Schettlinger, K., Fried, R., Gather, U. (2010) Real Time Signal Processing by Adaptive Repeated Median Filters, *International Journal of Adaptive Control and Signal Processing* **24**(5), 346-362.

Siegel, A.F. (1982) Robust Regression Using Repeated Medians, *Biometrika* **69**(1), 242-244.

See Also

robreg.filter, adore.filter, scarm.filter, mscarm.filter.

Examples

```
## Not run:
data(multi.ts)
extr <- madore.filter(multi.ts)
plot(extr)

## End(Not run)
```

med.filter *Median (MED) filter*

Description

This function extracts signals from time series by means of a running median.

Usage

```
med.filter(y, width, minNonNAs = 5, online = FALSE, extrapolate = TRUE)
```

Arguments

`y`	a numeric vector or (univariate) time series object.
`width`	a positive integer defining the window width used for fitting. If `online=FALSE` (see below) this needs to be an odd integer.
`minNonNAs`	a positive integer defining the minimum number of non-missing observations within one window which is required for a 'sensible' estimation.
`online`	a logical indicating whether the current level estimate is evaluated at the most recent time within each time window (`TRUE`) or centred within each window (`FALSE`). Setting `online=FALSE` requires the `width` to be odd. Default is `online=FALSE`.
`extrapolate`	a logical indicating whether the level estimations should be extrapolated to the edges of the time series. If `online=FALSE` the extrapolation consists of the fitted values within the first half of the first window and the last half of the last window; if `online=TRUE` the extrapolation consists of the fitted values within the first time window.

Details

`med.filter` is suitable for extracting low frequency components (the *signal*) from a time series which may be contaminated with outliers and can contain level shifts. For this, the median is computed in a moving window, and the signal level is estimated either at the end of each time window for online signal extraction without time delay (`online=TRUE`) or in the centre of each time window (`online=FALSE`).

Value

`med.filter` returns an object of class `robreg.filter`. An object of class `robreg.filter` is a list containing the following components:

`level`	a data frame containing the extracted signal level.
`slope`	a data frame containing the corresponding slope within each time window.

In addition, the original input time series is returned as list member `y`, and the settings used for the analysis are returned as the list members `width`, `minNonNAs`, `online` and `extrapolate`.

Application of the function `plot` to an object of class `robreg.filter` returns a plot showing the original time series with the filtered output.

Note

Missing values are treated by omitting them and thus by reducing the corresponding window width. The signal estimation is only returned as `NA` if the window the estimation is based on contains less than `minNonNAs` non-missing values.

Author(s)

Roland Fried, Karen Schettlinger and Matthias Borowski

References

Davies, P.L., Fried, R., Gather, U. (2004) Robust Signal Extraction for On-Line Monitoring Data, *Journal of Statistical Planning and Inference* **122**, 65-78.

Gather, U., Schettlinger, K., Fried, R. (2006) Online Signal Extraction by Robust Linear Regression, *Computational Statistics* **21**(1), 33-51.

Schettlinger, K., Fried, R., Gather, U. (2006) Robust Filters for Intensive Care Monitoring: Beyond the Running Median, *Biomedizinische Technik* **51**(2), 49-56.

See Also

`robreg.filter`

Examples

```
# Generate random time series:
y <- cumsum(runif(500)) - .5*(1:500)
# Add jumps:
y[200:500] <- y[200:500] + 5
y[400:500] <- y[400:500] - 7
# Add noise:
n <- sample(1:500, 30)
y[n] <- y[n] + rnorm(30)

# Online filtering with MED filter:
y.rr <- med.filter(y,width=41,online=FALSE)
plot(y.rr)
```

`mscarm.filter` *MSCARM (Multivariate Slope Comparing Adaptive Repeated Median)*

Description

A multivariate version of the `scarm.filter` which also gives information about parallel running components of the multivariate time series

Usage

```
mscarm.filter(time.series,
              right.width=30, min.left.width=right.width,
              min.width=floor(right.width/3), max.width=200,
              sign.level=0.001, bound.noise.sd=0.01,
              rtr=TRUE, autocorrelations="automatic",
              c.bound=3, r.bound=0)
```

Arguments

`time.series` a numeric matrix or multivariate time series object.

`right.width` a positive integer ≥ 5 defining the fixed width of the right-hand window used for the SCARM test; the choice of `right.width` is crucial to distinguish between a patch of outliers and a signal change.

`min.left.width` a positive integer $\geq$ `right.width` defining the minimum width of the left-hand window used for testing.

`min.width` a positive integer ≥ 5 specifying the minimum window width.

`max.width` a positive integer $\geq$ `min.width` and $\geq$ `right.width` + `min.left.width` specifying the maximum window width.

`sign.level` significance level of the SCARM test procedure; must be a value in $(0, 0.5)$.

`bound.noise.sd` a lower bound for the estimate of the noise standard deviation; this bound ensures that the noise scale estimate cannot be zero due to ties in the data; must be a value > 0.

`rtr` if `rtr=TRUE`, the signal estimation is restricted to the range of the rightmost `min.width` observations.

`autocorrelations` the `mscarm.filter` is developed for non-autocorrelated data, but can be adapted to work for AR(1) processes with parameter $\phi = -0.9, -0.6, ..., 0.9$; `autocorrelations` must be either "no" ($\phi = 0$), "high.positive" ($\phi = 0.9$), "moderate.positive" ($\phi = 0.6$), "small.positive" ($\phi = 0.3$), "small.negative" ($\phi = -0.3$), "moderate.negative ($\phi = -0.6$)", "high.negative ($\phi = -0.9$)" or "automatic"; if `autocorrelations="automatic"`, the true parameter ϕ is estimated at each time point.

`c.bound` the bound for the SSM (Similar Slope Monitoring) statistic which is the absolute difference of RM (Repeated Median) trend estimates (of two univariate time series) relative to the estimated standard deviation of this difference; if the SSM statistic is not larger than `c.bound`, a relationship between the two time series is assumed; `c.bound` must be a value >0.

`r.bound` the bound for the ratio of adapted window widths (of two univariate time series); a relationship between the two time series is only possible, if this ratio (smaller window width divided by larger window width) is smaller than `r.bound`; `r.bound` must be a value in $[0, 1]$.

Details

The mscarm.filter is a procedure for real-time signal extraction from noisy and outlier-contaminated instationary multivariate time series. It is based on *Repeated Median* regression (Siegel, 1982) in moving time windows. At each time point t the test procedure of the SCARM filter (Borowski and Fried, 2011) is used to determine an appropriate window width $n(t)$ in [min.width, max.width]. Then the signal vector at time t is estimated within the time window $(t - n(t) + 1, \ldots, t)$ by a slight modification of the multivariate *Trimmed Repeated Median-Least Squares* regression (Lanius, Gather, 2010). At each time point t, the mscarm.filter uses the *Similar Slope Monitoring* (SSM) method to build blocks of currently interrelated univariate time series. This information is given to the user and is used to improve the signal estimations. A detailed description of the mscarm.filter can be found in Borowski (2012).

Value

mscarm.filter returns an object of class mscarm.filter. An object of class mscarm.filter is a list containing the following components:

signal.est	a matrix containing the signal estimations
slope.est	a matrix containing the slope (or trend) estimations
adapted.width	a matrix containing the adapted window widths
noise.sd.est	a matrix containing the estimated noise standard deviations
scarm.signal.est	a matrix containing the signal estimates of the univariate SCARM
scarm.width	a matrix containing the adapted window widths of the univariate SCARM
scarm.statistic	a matrix containing the SCARM test statistics
scarm.critval	a matrix containing the critical values of the SCARM test
ssm.statistic	a matrix containing the SSM statistics
blocks	a matrix of the blocks built by the SSM procedure
acf.lag.one	a matrix containing the estimated autocorrelations at lag one for each time point; estimation is done on the recent max.width observations at each time point
time.series	the original input data

In addition, the input arguments used for the analysis are returned as list members.

Application of the function plot to an object of class mscarm.filter returns a plot showing the original time series with the filtered output. If info==TRUE (default), a plot showing the results of the SSM procedure is given.

Author(s)

Matthias Borowski

References

Borowski, M. (2012) Echtzeit-Extraktion relevanter Information aus multivariaten Zeitreihen basierend auf robuster Regression, *PhD thesis, TU Dortmund University (in German)*.

Borowski, M. and Fried, R. (2011) Robust repeated median regression in moving windows with data-adaptive width selection, *Discussion Paper 28/2011, SFB 823, TU Dortmund University*.

Lanius, V., Gather, U. (2010) Robust Online Signal Extraction from Multivariate Time Series, *Computational Statistics and Data Analysis* **54**(4), 966-975.

Siegel, A.F. (1982) Robust Regression Using Repeated Medians, *Biometrika* **69**(1), 242-244.

See Also

robreg.filter, adore.filter, madore.filter, scarm.filter.

Examples

```
## Not run:
# Multivariate time series
data(multi.ts)

# apply MSCARM Filter
mscarm.extr <- mscarm.filter(multi.ts)
plot(mscarm.extr)

## End(Not run)
```

---

multi.ts *Generated Multivariate Time Series*

Description

This data matrix contains a 4-variate time series of length 500. It consists of two Blocks and two Doppler signals each overlaid by highly correlated bivariate Gaussian noise.

Usage

```
multi.ts
```

Format

A (500x4)-matrix containing a 4-variate time series of length 500.

Source

Data generated by means of the packages `wmtsa` and `MASS`.

`rm.filter` *Repeated Median (RM) filter*

Description

This function extracts signals from time series by means of Repeated Median regression in a moving time window.

Usage

```
rm.filter(y, width, minNonNAs = 5, online = FALSE, extrapolate = TRUE)
```

Arguments

`y`	a numeric vector or (univariate) time series object.
`width`	a positive integer defining the window width used for fitting. If `online=FALSE` (see below) this needs to be an odd integer.
`minNonNAs`	a positive integer defining the minimum number of non-missing observations within one window which is required for a 'sensible' estimation.
`online`	a logical indicating whether the current level estimate is evaluated at the most recent time within each time window (`TRUE`) or centred within each window (`FALSE`). Setting `online=FALSE` requires the `width` to be odd. Default is `online=FALSE`.
`extrapolate`	a logical indicating whether the level estimations should be extrapolated to the edges of the time series. If `online=FALSE` the extrapolation consists of the fitted values within the first half of the first window and the last half of the last window; if `online=TRUE` the extrapolation consists of the fitted values within the first time window.

Details

`rm.filter` is suitable for extracting low frequency components (the *signal*) from a time series which may be contaminated with outliers and can contain level shifts. For this, robust Repeated Median regression is applied to a moving window, and the signal level is estimated by the fitted value either at the end of each time window for online signal extraction without time delay (`online=TRUE`) or in the centre of each time window (`online=FALSE`).

Value

`rm.filter` returns an object of class `robreg.filter`. An object of class `robreg.filter` is a list containing the following components:

`level`	a data frame containing the extracted signal level.
`slope`	a data frame containing the corresponding slope within each time window.

In addition, the original input time series is returned as list member `y`, and the settings used for the analysis are returned as the list members `width`, `minNonNAs`, `online` and `extrapolate`.

Application of the function `plot` to an object of class `robreg.filter` returns a plot showing the original time series with the filtered output.

Note

Missing values are treated by omitting them and thus by reducing the corresponding window width. The estimated signal level is only returned as NA if the window the estimation is based on contains less than minNonNAs non-missing values.

Author(s)

Roland Fried, Karen Schettlinger and Matthias Borowski

References

Davies, P.L., Fried, R., Gather, U. (2004) Robust Signal Extraction for On-Line Monitoring Data, *Journal of Statistical Planning and Inference* **122**, 65-78.

Gather, U., Schettlinger, K., Fried, R. (2006) Online Signal Extraction by Robust Linear Regression, *Computational Statistics* **21**(1), 33-51.

Schettlinger, K., Fried, R., Gather, U. (2006) Robust Filters for Intensive Care Monitoring: Beyond the Running Median, *Biomedizinische Technik* **51**(2), 49-56.

See Also

robreg.filter, scarm.filter, adore.filter, madore.filter

Examples

```
# Generate random time series:
y <- cumsum(runif(500)) - .5*(1:500)
# Add jumps:
y[200:500] <- y[200:500] + 5
y[400:500] <- y[400:500] - 7
# Add noise:
n <- sample(1:500, 30)
y[n] <- y[n] + rnorm(30)

# Online filtering with RM filter:
y.rr <- rm.filter(y,width=41,online=TRUE)
plot(y.rr)
```

---

robreg.filter *Robust Regression Filters for Univariate Time Series*

Description

Procedures for robust (online) extraction of low frequency components (the *signal*) from a univariate time series by applying robust regression techniques to moving time windows.

Usage

```
robreg.filter(y, width, method = "all", h = floor(width/2)+1,
                minNonNAs = 5, online = FALSE, extrapolate = TRUE)
```

Arguments

- `y` — a numeric vector or (univariate) time series object.
- `width` — a positive integer defining the window width used for fitting.
  If `online=FALSE` (see below) this needs to be an odd integer.
- `method` — a (vector of) character string(s) containing the method(s) to be used for robust approximation of the signal within one time window. It is possible to specify any combination of the values:
  - `"DR"` Deepest Regression
  - `"LMS"` Least Median of Squares regression
  - `"LQD"` Least Quartile Difference regression
  - `"LTS"` Least Trimmed Squares regression
  - `"MED"` Median
  - `"RM"` Repeated Median regression
  - `"all"` all of the above (default)

  Using `dr.filter`, `lms.filter`, `lqd.filter`, `lts.filter`, `med.filter` or `rm.filter` forces `"DR"`, `"LMS"`, `"LQD"`, `"LTS"`, `"MED"` or `"RM"` respectively.
  Currently, only `method="MED"` and `method="RM"` (`med.filter` / `rm.filter`) can handle missing values in the input time series. For the other regression filters missing values have to be replaced before the analysis.
- `h` — a positive integer defining the trimming quantile for LTS regression.
- `minNonNAs` — a positive integer defining the minimum number of non-missing observations within one window which is required for a 'sensible' estimation. Currently, this option only has an effect for the two methods `"MED"` and /or `"RM"` (see `method`).
- `online` — a logical indicating whether the current level estimate is evaluated at the most recent time within each time window (`TRUE`) or centred within each window (`FALSE`). Setting `online=FALSE` requires the `width` to be odd. Default is `online=FALSE`.
- `extrapolate` — a logical indicating whether the level estimations should be extrapolated to the edges of the time series.
  If `online=FALSE` the extrapolation consists of the fitted values within the first half of the first window and the last half of the last window; if `online=TRUE` the extrapolation consists of the fitted values within the first time window.

Details

`robreg.filter` is suitable for extracting low frequency components (the *signal*) from a time series which may be contaminated with outliers and can contain level shifts. For this, robust regression methods are applied to a moving window, and the signal level is estimated by the fitted value either at the end of each time window for online signal extraction without time delay (`online=TRUE`) or in the centre of each time window (`online=FALSE`).

Value

`robreg.filter` returns an object of class `robreg.filter`. An object of class `robreg.filter` is a list containing the following components:

`level`	a data frame containing the signal level extracted by the filter(s) specified in `method`.
`slope`	a data frame containing the corresponding slope within each time window.

In addition, the original input time series is returned as list member `y`, and the settings used for the analysis are returned as the list members `width`, `method`, `h`, `minNonNAs`, `online` and `extrapolate`.

Application of the function `plot` to an object of class `robreg.filter` returns a plot showing the original time series with the filtered output.

Note

Missing values are treated by omitting them and thus by reducing the corresponding window width. The estimated signal level is only returned as `NA` if the window the estimation is based on contains less than `minNonNAs` non-missing values.

Author(s)

C++ code: Thorsten Bernholt and Robin Nunkesser
Port to R: Roland Fried and Karen Schettlinger

References

Davies, P.L., Fried, R., Gather, U. (2004) Robust Signal Extraction for On-Line Monitoring Data, *Journal of Statistical Planning and Inference* **122**, 65-78.
(earlier version: http://hdl.handle.net/2003/5043)

Gather, U., Schettlinger, K., Fried, R. (2006) Online Signal Extraction by Robust Linear Regression, *Computational Statistics* **21**(1), 33-51.
(earlier version: http://hdl.handle.net/2003/5305)

Schettlinger, K., Fried, R., Gather, U. (2006) Robust Filters for Intensive Care Monitoring: Beyond the Running Median, *Biomedizinische Technik* **51**(2), 49-56.

See Also

`wrm.filter`, `robust.filter`, `dw.filter`, `hybrid.filter`.

Examples

```
# Generate random time series:
y <- cumsum(runif(500)) - .5*(1:500)
# Add jumps:
y[200:500] <- y[200:500] + 5
y[400:500] <- y[400:500] - 7
# Add noise:
n <- sample(1:500, 30)
y[n] <- y[n] + rnorm(30)

# Filtering with all methods:
y.rr <- robreg.filter(y, width=31, method=c("RM", "LMS", "LTS", "DR", "LQD"))
# Plot:
plot(y.rr)

# Delayed filtering with RM and LMS filter:
y2.rr <- robreg.filter(y,width=31,method=c("RM","LMS"))
plot(y2.rr)

# Online filtering with RM filter:
y3.rr <- rm.filter(y,width=41,online=TRUE)
plot(y3.rr)
```

---

robust.filter *Robust Filtering Methods for Univariate Time Series*

Description

Procedure for robust (online) extraction of low frequency components (the *signal*) from a univariate time series with optional rules for outlier replacement and shift detection.

Usage

```
robust.filter(y, width, trend = "RM", scale = "QN", outlier = "T",
                        shiftd = 2, wshift = floor(width/2), lbound = 0.1, p = 0.9,
                           adapt = 0, max.width = width,
                           online = FALSE, extrapolate = TRUE)
```

Arguments

`y` a numeric vector or (univariate) time series object.

`width` a positive integer defining the window width used for fitting. If `online=FALSE` (default) this needs to be an odd number.

`trend` a character string defining the method to be used for robust approximation of the signal within one time window. Possible values are:

`"MED"`: Median

"RM": Repeated Median regression (default)
"LTS": Least Trimmed Squares regression
"LMS": Least Median of Squares regression

scale
: a character string defining the method to be used for robust estimation of the local variability (within one time window). Possible values are:

"MAD": Median absolute deviation about the median
"QN": Rousseeuw's and Croux' (1993) Q_n scale estimator (default)
"SN": Rousseeuw's and Croux' (1993) S_n scale estimator
"LSH": Length of the shortest half

outlier
: a single character defining the rule to be used for outlier detection and outlier treatment. Observations deviating more than $d \cdot \hat{\sigma}_t$ from the current level approximation $\hat{\mu}_t$ are replaced by $\hat{\mu}_t \pm k\hat{\sigma}_t$ where $\hat{\sigma}_t$ denotes the current scale estimate. Possible values are:

"T": Replace ('trim') large outliers detected by a 3σ-rule ($d = 3$) by the current level estimate ($k = 0$). (default)
"L": Shrink large outliers ($d = 3$) strongly towards the current level estimate ($k = 1$).
"M": Shrink large and moderatly sized outliers ($d = 2$) strongly towards the current level estimate ($k = 1$).
"W": Shrink large and moderatly sized outliers ($d = 2$) towards the current level estimate ($k = 2$).

W is the most efficient, T the most robust method (which should ideally be combined with a suitable value of lbound).

shiftd
: a positive numeric value defining the factor the current scale estimate is multiplied with for shift detection. Default is shiftd=2 corresponding to a 2σ rule for shift detection.

wshift
: a positive integer specifying the number of the most recent observations used for shift detection (regulates therefore also the delay of shift detection). Only used in the online mode; should be less than half the (minimal) window width then. In the offline mode (online=FALSE, default), shift detection is based on the right half of the time window, i.e. wshift=floor(width/2) (default).

lbound
: a positive real value specifying an optional lower bound for the scale to prevent the scale estimate from reaching zero (implosion).

p
: a fraction $\in [2/3, 1]$ of observations for additional rules in case of only two or three different values within one window.
If 100 percent of the observations within one window take on only two different values, the current level is estimated by the mean of these values regardless of the trend specification. In case of three differing values the median is taken as the current level estimate.

adapt
: a numeric value defining the fraction which regulates the adaption of the moving window width. adapt can be either 0 or a value $\in [0.6, 1]$. adapt = 0 means that a fixed window width is used. Otherwise, the window width is reduced whenever more than a fraction of adapt $\in [0.6, 1]$ of the residuals in a certain part of the current time window are all positive or all negative.

max.width	a positive integer (>= width) specifying the maximal width of the time window. width specifies the minimal (and also the initial) width.
online	a logical indicating whether the current level and scale estimates are evaluated at the most recent time within each window (TRUE) or centered within the window (FALSE). online=FALSE (default) requires an odd width for the window and means a time delay of (width+1)/2 time units.
extrapolate	a logical indicating whether the level estimations should be extrapolated to the edges of the time series. If online=FALSE the extrapolation consists of the fitted values within the first half of the first window and the last half of the last window; if online=TRUE the extrapolation consists of all fitted values within the first time window.

Details

robust.filter works by applying the methods specified by trend and scale to a moving time window of length width.

Before moving the time window, it is checked whether the next (incoming) observation is considered an 'outlier' by applying the rule specified by outlier. Therefore, the trend in the current time window is extrapolated to the next point in time and the residual of the incoming observation is standardised by the current scale estimate.

After moving the time window, it can be tested whether a level shift has occurred within the window: If more than half of the residuals in the right part of the window are larger than shiftd$\cdot\sigma_t$, a shift is detected and appropriate actions are taken. In the online mode, the number of the rightmost residuals can be chosen by wshift to regulate the resistance of the detection rule against outliers, its power and the time delay of detection.

A more detailed description of the filter can be found in Fried (2004). The adaption of the window width is described by Gather and Fried (2004). For more explanations on shift detection, see Fried and Gather (2007).

Value

robust.filter returns an object of class robust.filter. An object of class robust.filter is a list containing the following components:

level	a numeric vector containing the signal level extracted by the (regression) filter specified by trend, scale and outlier.
slope	a numeric vector containing the corresponding slope within each time window.
sigma	a numeric vector containing the corresponding scale within each time window.
ol	an outlier indicator. 0: no outlier, +1: positive outlier, -1: negative outlier
level.shift	a level shift indicator. 0: no level shift, t: positive level shift detected at processing time t, -t: negative level shift detected at processing time t (the position in the vector gives an estimate of the point in time before which the shift has occurred).

In addition, the original input time series is returned as list member y, and the settings used for the analysis are returned as the list members width, trend, scale, outlier, shiftd, wshift, lbound, p, adapt, max.width, online and extrapolate.

Application of the function `plot` to an object of class `robust.filter` returns a plot showing the original time series with the filtered output.

Note

Missing values have to be replaced or removed from the time series before applying `robust.filter`.

Author(s)

Roland Fried and Karen Schettlinger

References

Fried, R. (2004), Robust Filtering of Time Series with Trends, *Journal of Nonparametric Statistics* **16**, 313-328.
(earlier version: http://hdl.handle.net/2003/4992)

Fried, R., Gather, U. (2007), On Rank Tests for Shift Detection in Time Series, *Computational Statistics and Data Analysis, Special Issue on Machine Learning and Robust Data Mining* **52**, 221-233.
(earlier version: http://hdl.handle.net/2003/23301)

Gather, U., Fried, R. (2004), Methods and Algorithms for Robust Filtering, *COMPSTAT 2004: Proceedings in Computational Statistics*, J. Antoch (eds.), Physika-Verlag, Heidelberg, 159-170.

Schettlinger, K., Fried, R., Gather, U. (2006) Robust Filters for Intensive Care Monitoring: Beyond the Running Median, *Biomedizinische Technik* **51**(2), 49-56.

See Also

`robreg.filter`, `hybrid.filter`, `dw.filter`, `wrm.filter`.

Examples

```
# Generate random time series:
y <- cumsum(runif(500)) - .5*(1:500)
# Add jumps:
y[200:500] <- y[200:500] + 5
y[400:500] <- y[400:500] - 7
# Add noise:
n <- sample(1:500, 30)
y[n] <- y[n] + rnorm(30)

# Delayed Filtering of the time series with window width 23:
y.rf <- robust.filter(y, width=23)
# Plot:
plot(y.rf)

# Delayed Filtering with different settings and fixed window width 31:
y.rf2 <- robust.filter(y, width=31, trend="LMS", scale="QN", outlier="W")
plot(y.rf2)
```

```
# Online Filtering with fixed window width 24:
y.rf3 <- robust.filter(y, width=24, online=TRUE)
plot(y.rf3)

# Delayed Filtering with adaptive window width (minimal width 11, maximal width 51):
y.rf4 <- robust.filter(y, width=11, adapt=0.7, max.width=51)
plot(y.rf4)
```

`scarm.filter` *SCARM (Slope Comparing Adaptive Repeated Median)*

Description

A procedure for robust online signal extraction from univariate time series ("smoothing") by a moving window technique with adaptive window width selection based on Repeated Median regression

Usage

```
scarm.filter(time.series,
             right.width=30, min.left.width=right.width,
             min.width=floor(right.width/3), max.width=200,
             sign.level=0.001, bound.noise.sd=0.01, rtr=TRUE,
             autocorrelations="automatic")
```

Arguments

`time.series`	a numeric vector or (univariate) time series object.
`right.width`	a positive integer >=5 defining the fixed width of the right-hand window used for testing; the choice of `right.width` is crucial to distinguish between a patch of outliers and a signal change.
`min.left.width`	a positive integer $\geq$ `right.width` defining the minimum width of the left-hand window used for testing.
`min.width`	a positive integer ≥ 5 specifying the minimum window width.
`max.width`	a positive integer $\geq$ `min.width` and $\geq$ `right.width` + `min.left.width` specifying the maximum window width.
`sign.level`	significance level of the test procedure; must be a value in $(0, 0.5)$.
`bound.noise.sd`	a lower bound for the estimate of the noise standard deviation; this bound ensures that the noise scale estimate cannot be zero due to ties in the data; must be a value > 0.
`rtr`	if `rtr=TRUE`, the signal estimation is restricted to the range of the rightmost `min.width` observations.
`autocorrelations`	the `scarm.filter` is developed for non-autocorrelated data, but can be adapted to work for AR(1) processes with parameter $\phi = -0.9, -0.6, ..., 0.9$; `autocorrelations` must be either "no" ($\phi = 0$), "high.positive" ($\phi = 0.9$), "moderate.positive"

($\phi = 0.6$), "small.positive" ($\phi = 0.3$), "small.negative" ($\phi = -0.3$), "moderate.negative ($\phi = -0.6$)", "high.negative ($\phi = -0.9$)" or "automatic"; if `autocorrelations="automatic"`, the true parameter ϕ is estimated at each time point.

Details

The `scarm.filter` fits a Repeated Median (RM, Siegel, 1982) regression line to a moving window sample with length varying between `min.width` and `max.width`.

For each time point, the window width is adapted to the current data situation by a test comparing two RM slopes estimated in separated sub-windows, a right-hand and a left-hand window.

A more detailed description of the filter can be found in Borowski and Fried (2011).

Value

`scarm.filter` returns an object of class `scarm.filter`. An object of class `scarm.filter` is a list containing the following components:

`signal.est`	a vector containing the signal estimations
`slope.est`	a vector containing the slope (or trend) estimations
`adapted.width`	a vector containing the adapted window widths
`test.statistic`	a vector containing the SCARM test statistics
`critvals`	a vector containing the critical values for test decision
`noise.sd`	a vector containing the estimates of the noise standard deviation
`slope.diff`	a vector containing the differences of the Repeated Median slopes estimated in the left-hand and right-hand window
`acf.lag.one`	a vector containing the estimated autocorrelations at lag one for each time point; estimation is done on the recent `max.width` observations at each time point
`time.series`	the original input data

In addition, the input arguments used for the analysis are returned as list members.

Application of the function `plot` to an object of class `scarm.filter` returns a plot showing the original time series with the filtered output. If `info==TRUE` (default), a plot of the adapted window widths is also given.

Author(s)

Matthias Borowski

References

Borowski, M. and Fried, R. (2011) Robust repeated median regression in moving windows with data-adaptive width selection, *Discussion Paper 28/2011, SFB 823, TU Dortmund University*.

Gelper, S., Schettlinger, K., Croux, C., and Gather, U. (2009) Robust online scale estimation in time series: A model-free approach, *Journal of Statistical Planning and Inference*, **139**(2), 335-349.

Siegel, A.F. (1982) Robust Regression Using Repeated Medians, *Biometrika* **69**(1), 242-244.

See Also

robreg.filter, adore.filter, madore.filter, mscarm.filter.

Examples

```
# Time series
data(multi.ts)
x <- multi.ts[,1]

# apply SCARM Filter
scarm.extr <- scarm.filter(x)
plot(scarm.extr)
```

---

sizecorrection — *Bias correction factors for the robust scale estimators MAD, Sn, Qn, and LSH*

Description

This matrix contains correction factors for the MAD, Sn, Qn, and LSH scale estimators to achieve unbiasedness under Gaussian noise.

Usage

```
sizecorrection
```

Format

A (31x4)-matrix containing correction factors for the MAD, Sn, Qn, and LSH scale estimators.

Source

The correction factors have been obtained by simulations.

`timecorrection` *Correction factors for the scale estimation of the filtering procedure proposed by Fried (2004).*

Description

Fried's (2004) signal extraction procedure includes optional rules for outlier replacement based on local scale estimation. Since detected outliers are treated as missing values, the finite sample correction for the scale estimation is adjusted for the reduced sample size, using the correction factors in the dataset 'timecorrection'.

Usage

```
timecorrection
```

Format

A (250x16)-matrix containing the correction factors for the scale estimators MAD, Qn, Sn, and LSH and for the outlier treatments 'trimming', 'downsizing large values', 'downsizing moderate values', and 'winsorization'.

Source

The correction factors have been obtained by simulations.

References

Fried, R. (2004), Robust Filtering of Time Series with Trends, *Journal of Nonparametric Statistics* **16**, 313-328.

See Also

`robust.filter`.

`var.n` *Variance of the Repeated Median slope estimator.*

Description

Empirical variance of the Repeated Median slope estimator, computed on standard normal noise in moving windows of width n; required by the function `scarm.filter`.

Usage

```
data(var.n)
```

Format

The format is: num [1:300] NA NA NA NA 0.138 ...

Details

The variance of the Repeated Median slope estimator depends on the size of the window sample, i.e. the window width n. These are results from simulations, where the Repeated Median slope has been computed on standard normal noise in moving windows of width n. The value `var.n[n]` is the variance for the window width n.

Source

The empirical variances have been obtained by simulations.

References

Borowski, M. and Fried, R. (2011) Robust moving window regression for online signal extraction from non-stationary time series: online window width adaption by testing for signal changes, *submitted*.

`wrm.filter` *Weighted Repeated Median Filters for Univariate Time Series*

Description

Filtering procedure based on a weighted version of Siegel's (1982) repeated median (RM) and a moving time window for robust extraction of low frequency components (the signal) in the presence of outliers and shifts. One of several weight functions can be chosen to weight the observations in each time window.

Usage

```
wrm.filter(y, width, weight.type = 1, del = floor(width/2), extrapolate = TRUE)
```

Arguments

`y`	a numeric vector or (univariate) time series object.
`width`	a positive integer defining the window width used for fitting. If `del = floor(width/2)` (default) this needs to be an odd number.
`weight.type`	Indicates the weight function used. `weight.type=0`**:** equal weighting `weight.type=1`**:** triangular weights (default) `weight.type=2`**:** Epanechnikov weights
`del`	a positve integer (smaller than width) specifying the delay of the signal extraction. `del=0` means online signal extraction without delay. Default is `del=floor(width/2)`.

`extrapolate`	a logical indicating whether the level estimations should be extrapolated to the edges of the time series. If `del = floor(width/2)` (default) the extrapolation consists of the fitted values within the first half of the first window and the last half of the last window; if `del=0` the extrapolation consists of the all fitted values within the first time window.

Details

For online signal extraction without time delay, weighted repeated median filtering with triangular weights is recommendable in the presence of isolated outliers and abrupt level shifts since it reacts more quickly to shifts than unweighted repeated median filtering and provides higher efficiencies. The window width should be chosen based on a guess of the minimal time period in which the signal can be approximated by a straight line without abrupt shifts. Better results can be obtained by increasing the delay, but often minimization of the time delay itself is one of the objectives so that one prefers del=0. The procedure replaces missing values by simple extrapolations if these are not within the first time window used for initialization.

For "offline" situations, it is intuitive to set `del` roughly equal to `width/2`. If the focus is rather on smoothing than on signal extraction, the Epanechnikov kernel should be used rather than the triangular kernel. In this case one can also use directly function `wrm.smooth`.

Value

`wrm.filter` returns an object of class `wrm.filter`. An object of class `wrm.filter` is a list containing the following components:

`y`	the original input time series.
`level`	the corresponding signal level extracted by the filter.
`slope`	the corresponding slope within each time window.
`del`	the parameter specifying the delay of the signal extraction.
`width`	width of the time window.
`weight.type`	name of the weight function used for the fit.

The function `plot` returns a plot showing the original time series with the filtered output.

Author(s)

Roland Fried and Jochen Einbeck

References

These filtering procedures are described and investigated in
Fried, R., Einbeck, J., Gather, U. (2007), Weighted Repeated Median Smoothing and Filtering, *Journal of the American Statistical Association* **102**, 1300-1308.
Preliminary version available as technical report from https://eldorado.tu-dortmund.de/handle/2003/21637

See Also

dw.filter, hybrid.filter, wrm.smooth

Examples

```
data(Nile)
nile <- as.numeric(Nile)
obj <- wrm.filter(nile, width=11)
plot(obj)
```

---

wrm.smooth *Weighted Repeated Median Smoothing*

Description

A robust smoothing tool using a kernel weighted version of Siegel's (1982) repeated median. It can be seen as an alternative to local linear L1 regression.

Usage

```
wrm.smooth(x, y, h, xgrid, weight = 2)
```

Arguments

x	Vector of predictors.
y	Vector of responses, needs to have the same length as x.
h	Bandwidth, measured in the same units as the explanatory (independent) variable x: (x[0]-h,x[0]+h) is the range of x-values to be included in the local smoothing at x[0]. Needs to be a positive number.
xgrid	Grid on which fitted values are to be evaluated. The default is here to take the input values x for a sample size of at most 100, and seq(min(x),max(x), l=100) otherwise.
weight	Indicates the weight function used. weight=1 triangular weights weight=2 Epanechnikov weights (default) weight=3 Gaussian weights weight=4 Biweight weight=5 Uniform weights

Details

Weighted repeated median (WRM) smoothing was suggested in a signal extraction framework by Fried, Einbeck & Gather (2007). It combines the advantages of weighted and repeated medians, i.e. the WRM smoother is robust to outliers and adapts to linear trends (through the slope parameter of the repeated median, which is calculated by applying two consecutive weighted medians onto the pairwise slopes). The theory and simulations provided by Fried, Einbeck & Gather focus on online signal extraction from time series. Warning: The case of a kernel weighted repeated median smoother for arbitraty non-equidistant design (as implemented here) is not fully investigated yet.

The procedure copes with missing values by omitting them.

Value

`wrm.smooth` returns an object of class `wrm.smooth`. An object of class `wrm.smooth` is a list containing the following components:

`y`	the original input time series.
`level`	the corresponding signal level extraceted by the weighted Repeated Median filter.
`slope`	the corresponding WRM slope within each time window.
`h`	bandwidth.
`xgrid`	vector with grid values.
`weight`	name of the weight function used for the fit.

The function `plot` returns a plot showing the original data with the smoothed output.

Author(s)

Jochen Einbeck and Roland Fried

References

Fried, R., Einbeck, J., Gather, U. (2007), Weighted Repeated Median Smoothing and Filtering, *Journal of the American Statistical Association* **102**, 1300-1308.
Preliminary version available as technical report from https://eldorado.tu-dortmund.de/handle/2003/21637

Siegel, A.F. (1982). Robust regression using repeated medians. *Biometrika* **68**, 242-244.

See Also

`wrm.filter`

Examples

```
data(faithful) # Old Faithful Geyser data
faith.WRM <- wrm.smooth(faithful$w, faithful$e,h=4)
plot(faith.WRM)
```

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