Automatic recognition of plasma relevant events: implications for ITER

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Motivation

- Nowadays, processing all information of a fusion database is a much more important issue than acquiring data
  - Massive databases
- Fusion devices produce tens of thousands of discharges but only a very limited part of the collected information is analysed
  - Physics studies normally limited to a few tens of shots
- Plasma behaviours are recognised in experimental signals by the identification of known patterns
  - Diagnostics produce the same morphological patterns in the signals for reproducible plasma behaviours
- The analysis of physical events requires their identification and temporal location
  - The recognition and location of events are the main concerns in relation to the analysis: **manual**, complex and very time consuming searching processes
- Long pulse devices (W7X or ITER) will have databases with very large number of signals and very long records
  - ITER: discharges 30 minutes long and up to 10^6 signals per discharge

Motivation

- Can we identify relevant temporal segments in an automatic way?
  - '*relevant*' means '*with interest from some point of view*': either physics or machine control

- An automatic first screening of discharges would allow focusing the analysis on a reduced set of time intervals
  - Irrelevant parts of the shot are discarded
  - Improvement of statistical relevance for known events
    - Practically all the information inside the databases can be used
  - Potential detection of unknown events that appear on a regular basis

- Automatic recognition of relevant temporal segments means
  - Reduction of human efforts
  - Standardization of criteria
    - It reduces the vulnerability to human errors: missing occurrences, subjective assessments or location errors

Overview

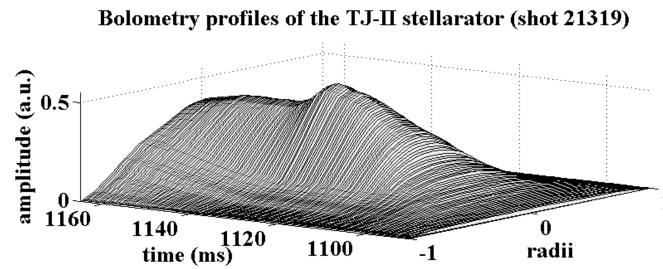
- Recognition of relevant events
- Algorithm to identify relevant events by detecting anomalies in signals
- Specific methods to detect anomalies in signals
- Conclusions

How to proceed?

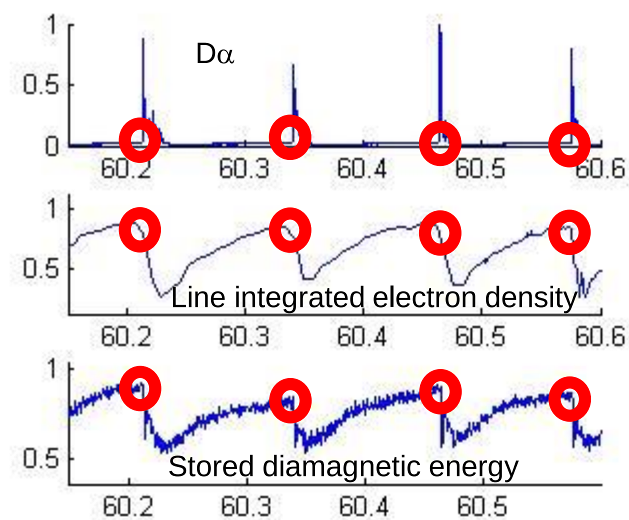
- Big Data techniques deal with heterogeneous, complex and massive datasets to identify patterns that are hidden inside enormous volumes of data
- ITER is expected to acquire more than 1 TB of data per discharge
- Signals can be time/amplitude series, temporal evolution of profiles (amplitude/radius relationship) and video-movies (infra-red and visible cameras)
- W7X or ITER databases satisfy the conditions of heterogeneity, complexity, size and hidden patterns to use Big Data techniques

How to recognise relevant events?

- A relevant event can be any kind of perturbation in the plasma evolution
- This is revealed in the temporal evolution of signals by means of unexpected variations (anomalies)
  - Time series
    - Amplitude, noise, presence/suppression of patterns with periodical structure
  - Profiles
    - Amplitude, hollow profiles, peaked profiles, wider profiles, gradients
  - Video-movies
    - Emission increasing
- An automatic search for events will have to locate anomalies in individual signals
- Interesting plasma behaviours are usually recognised by simultaneous anomalies in several signals



Edge localised modes (ELMs)



time (a.u.)

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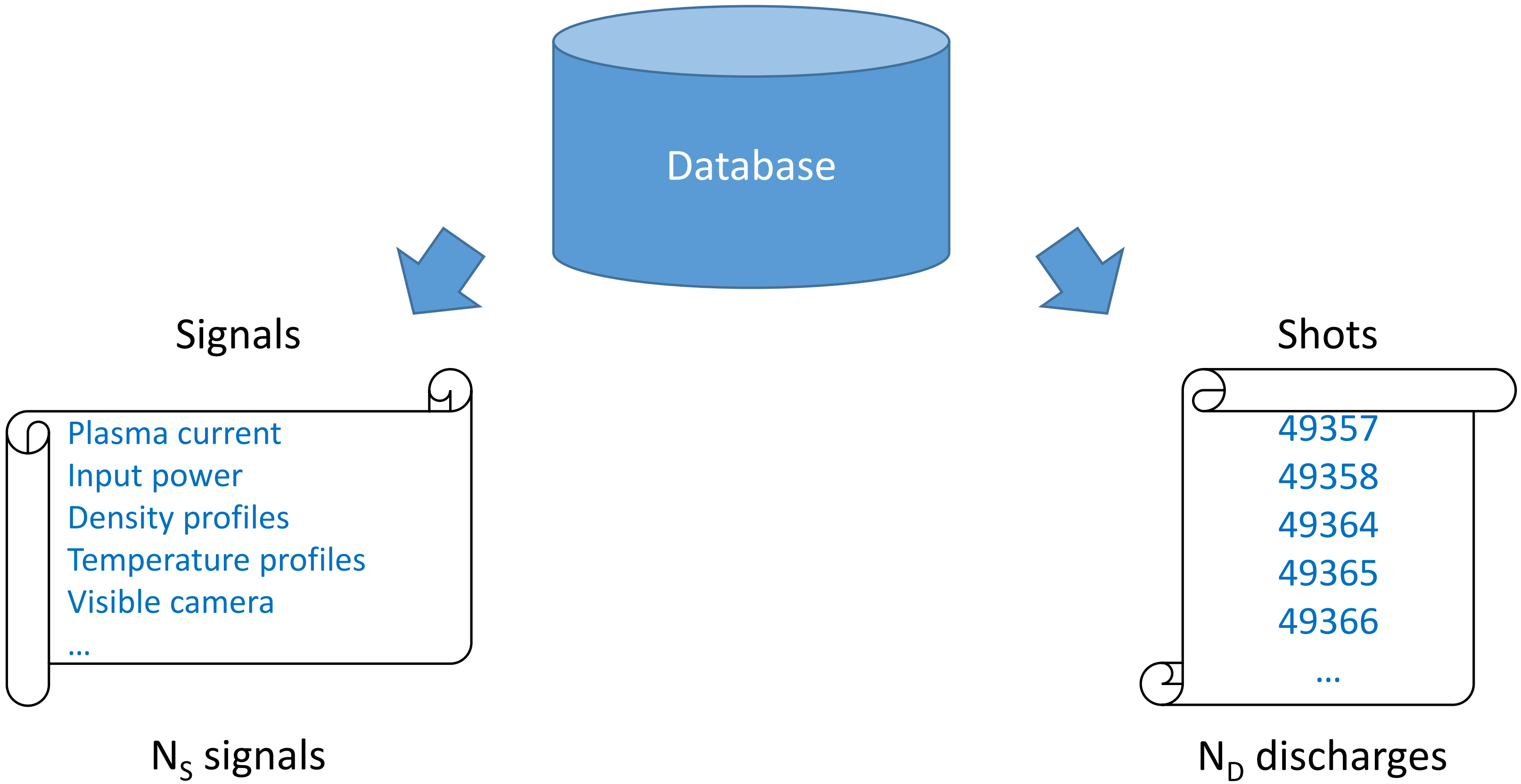
Algorithm for off-line automatic recognition of relevant events: 6 step process

To perform automatic recognition, software codes have to be executed in an unattended way

- 1st step: to define a dataset of signals and a range of discharges



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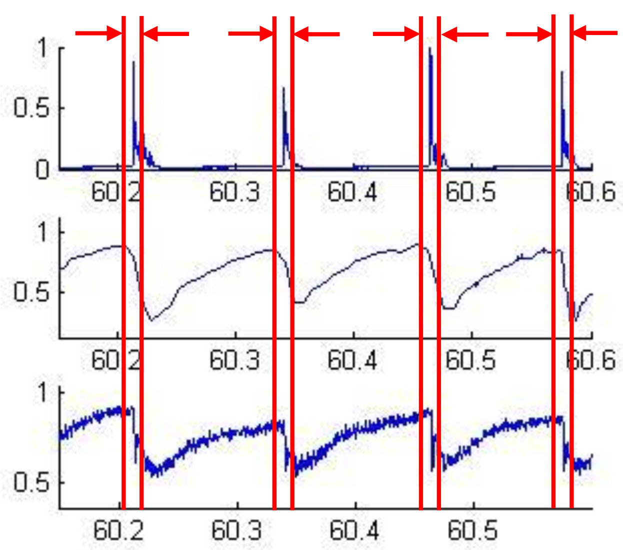
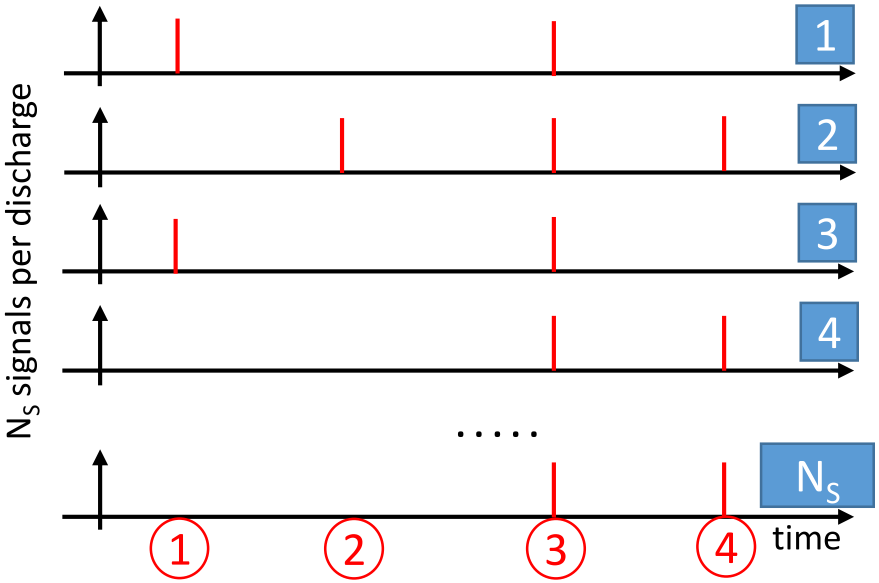
- 2nd step: to determine times in each discharge where individual signals show anomalies





Anomaly times in each signal of a discharge
- 4 anomalies in this case

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- 3rd step: to chose the morphological patterns within a time interval t_S around the anomaly time

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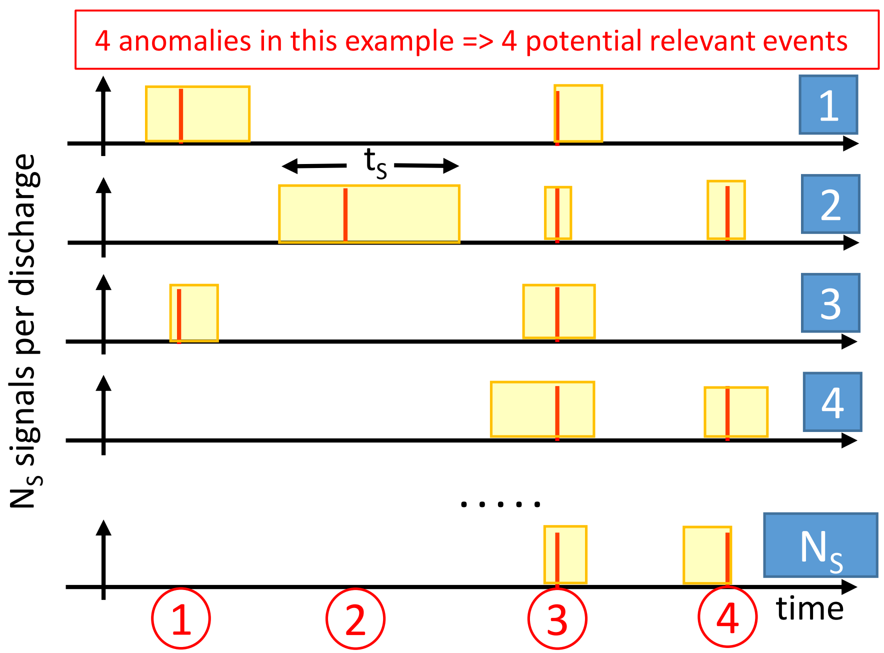
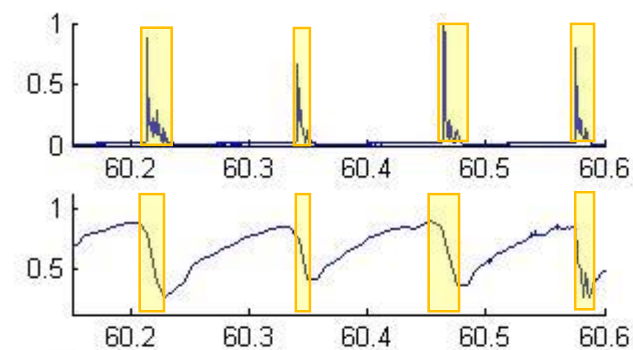
- 3rd step: to chose the morphological patterns within a time interval t_S around the anomaly time
  - The time interval t_S corresponding to the same plasma event could be quite different in several occurrences (in the same shot or in different shots)
    - The definition of the time interval means two selections: the starting time and the temporal length t_S
  - How to decide the interval of the different signals in an unattended way?





Dataset

- N_S signals/discharge
- N_D discharges

if $A_j, j = 1, \ldots, N_D$ is the number of anomalies in shot j

Total number of potential relevant events : $A_{TOTAL} = \sum_{j=1}^{N_D} A_j$

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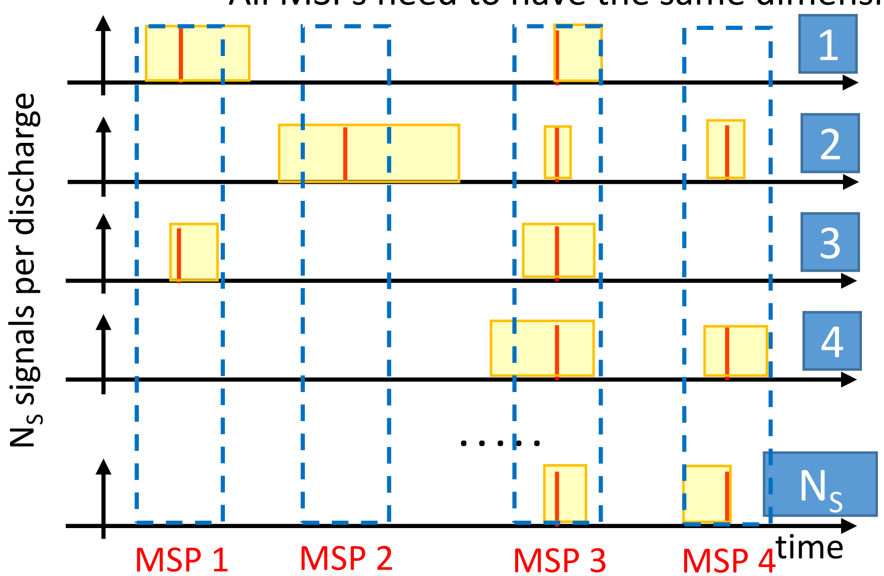
- 3rd step: to chose the morphological pattern of each individual signal within a time interval t_S around the anomaly time
- 4th step: to define multi-signal patterns (MSP)

Algorithm for off-line automatic recognition of relevant events: 6 step process

- 4th step: to define multi-signal patterns (MSP)
  - A MSP is made up of all patterns of all signals determined in step 3 around a common anomaly time
    - Signals without recognition of anomaly are also part of the MSP
  - A MSP is characterised by the morphological patterns of all the signals with a common time interval
  - A criterion to define the common time interval is necessary taking into account **all** MSPs in **all** discharges of the dataset
    - All MSPs need to have the same dimensionality



By assuming 200 sampling times per MSP and N_S = 100 signals with

- 95 time series
- 3 profiles (120 points each)
- 2 video-movies (500x300 each)

and 2 bytes per sample, the total amount of memory is 120 Mbytes/MSP

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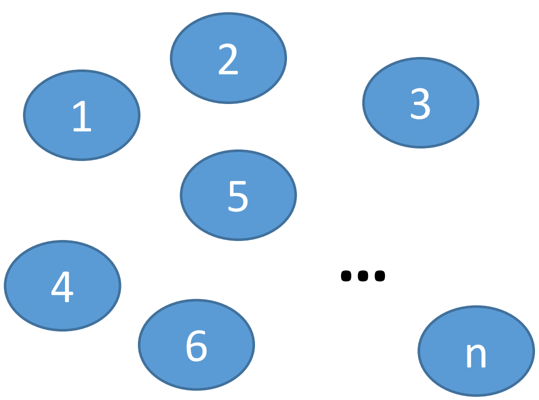
- 5th step: to group the MSPs into a number of sensible clusters in an unsupervised way (this reveals the organisation of the MSPs)

Algorithm for off-line automatic recognition of relevant events: 6 step process

- 5th step: to group the MSPs into a number of sensible clusters in an unsupervised way (this reveals the organisation of the MSPs)
  - The grouping of the MSPs into clusters provides the classification of the relevant events
  - The different clusters can be labelled but the challenge is to identify each cluster with a physical behaviour of the plasma
    - To be done by experts **NOT** in unattended way
  - Clusters that are identified with physical behaviours can be used to increase the statistical relevance of the data analysis
  - Clusters that are not identified with physical behaviours but show statistical weight suggest the presence of plasma behaviours not recognised so far
  - Clusters without statistical weight can be considered outliers



- By assuming 1 relevant event/10 s the unsupervised classification process requires 720 Mbytes/minute per shot
- Thinking of ITER shots (30 minutes long), this implies 21 Gbytes of memory per shot
- By considering N_D = 500 discharges, the total memory amount to solve the unsupervised clustering is **10 Tbytes!!**
  - The *curse of dimensionality*
- High performance computing is needed

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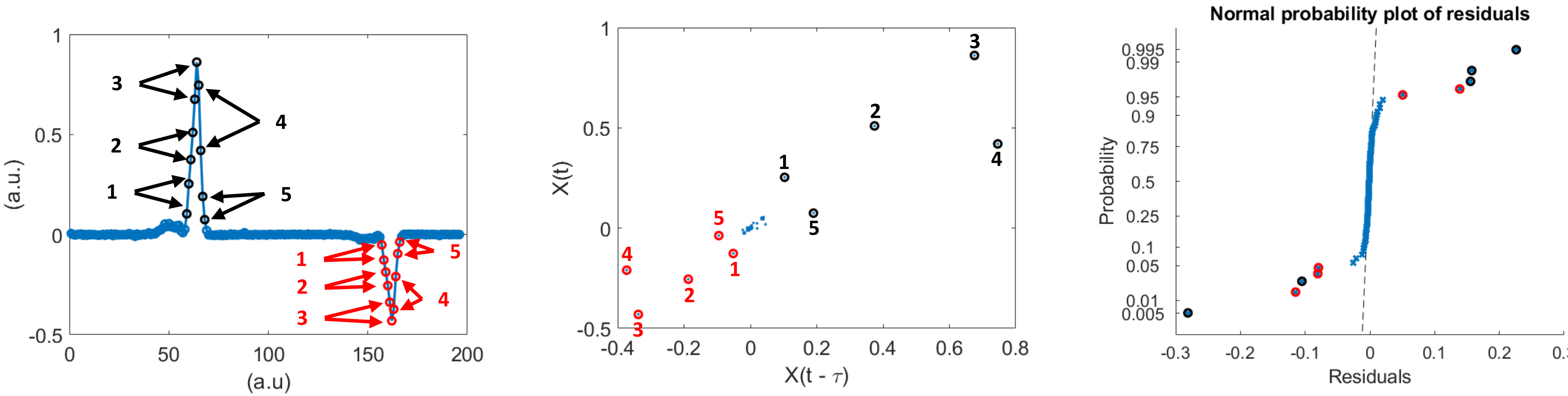
- 5th step: to group the MSPs into a number of sensible clusters in an unsupervised way (this reveals the organisation of the MSPs
- 6th step: to develop supervised classifiers with the classes of step 5
  - Classification of new MSPs with confidence measures allows assessing the reliability of the whole process
  - In this step, classes of MSPs are well-defined
  - Supervised classifiers can be implemented under real-time conditions

How to determine anomalies in individual signals?

- Anomalies in the temporal evolution of signals translate the existence of changes in the plasma behaviour
  - The more abrupt the change of shape in a signal the more abrupt the change in the plasma evolution
- Our analysis has been based on recognising changes in individual signals
  - This allows establishing the potential set of signals related to each plasma behaviour
- Each anomaly has to include a time interval around its time value
  - The objective is to try the characterisation of the several plasma behaviours by combining the several shapes of the signals around the anomalies
- Methods to locate anomalies in signals should provide an estimation of the time interval around the anomaly

Methods to determine anomaly times and related time interval: 1

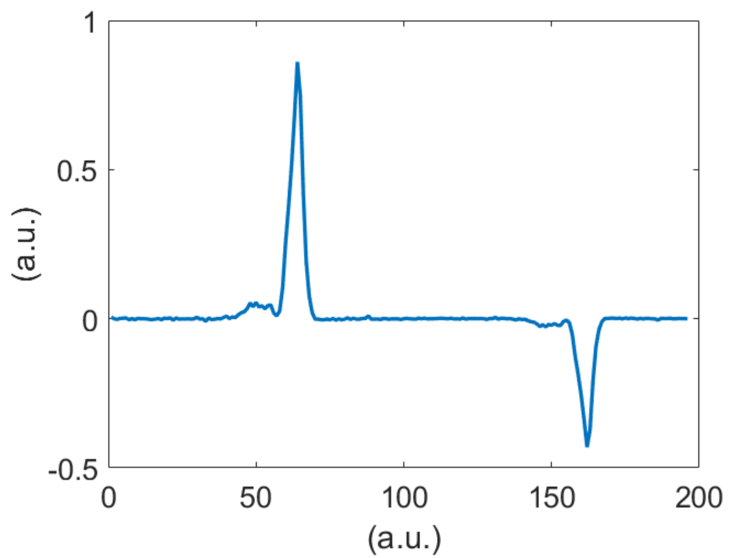
- Detection of outliers through a generalised linear regression model
  - If the temporal evolution is smooth, amplitudes between consecutive samples are very similar
  - In an space Y(t – τ)-Y(t), samples are distributed along the diagonal
  - Samples outside the diagonal are outliers
    - These are identified as outliers in the normal probability plots of residuals

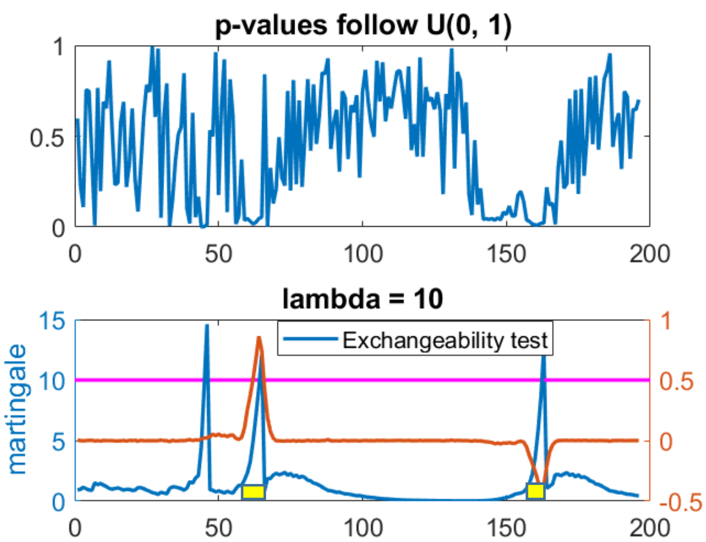


- The number of consecutive samples that are outliers determine the time interval
  - If the sampling period is τ, in both cases the time interval is 10·τ

Methods to determine anomaly times and related time interval: 2

- Use of martingales for testing exchangeability
  - The only assumption in the data stream is the *iid* hypothesis
    - Samples are independent and identically distributed (*iid*)
  - Anomalies are detected as the samples are produced
  - Anomalies are recognised when the martingale crosses the lambda threshold
  - The assumed rate of false alarms is 1/lambda





- The time interval of the anomaly corresponds to the time in which the martingale increases to achieve the lambda value

Other methods

- To follow the temporal evolution of the Fourier components of a signal
  - See R. Castro et al. (P/2-2)
- Using deep learning methods
  - See G. Farias et a. (O/3-1)

Conclusions

- Big data techniques will be essential for the automatic location and classification of plasma anomaly behaviours
- Methods for the automatic discovering of anomalies in signals have been discussed
- An algorithm to relate multi-signal patterns in an automatic way has been established
- Unsupervised classifications will allow labelling the clusters
  - High performance computing is needed
  - The correspondence between labels and physics behaviours has to be decided by experts
- Unsupervised clusters can be converted into reliable supervised classifiers
  - Real-time applications are possible

Thank you very much for your attention!