Machine Learning approach to classifying quench antenna signals

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Contents

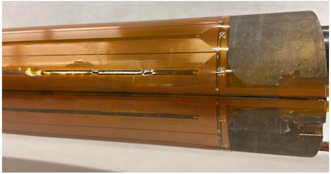
Superconducting materials

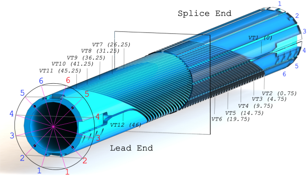
Superconductor:

- Material which achieves superconductivity, a state of matter that has no electrical resistance
- Extremely important for accelerators, because they can generate strong magnetic fields which provide strong bending and focusing of the beam
- Requires very low temperatures: Fermilab best magnets need 1.9 K to provide 14.6 T

Quench antennas

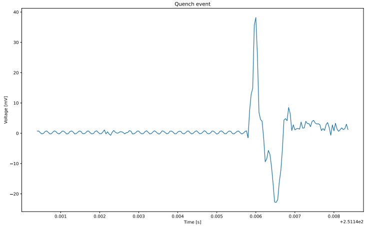
- Quench: sudden and irreversible transition of the superconductor into the normal-conducting state
  - After the quench, the energy stored in the magnet must be dissipated in order to protect the magnet
- Quench antennas: pick-up coil arrays sensitive to changes in the magnetic flux ⇒ provides quench identification and localization





Voltage changes along the ramp

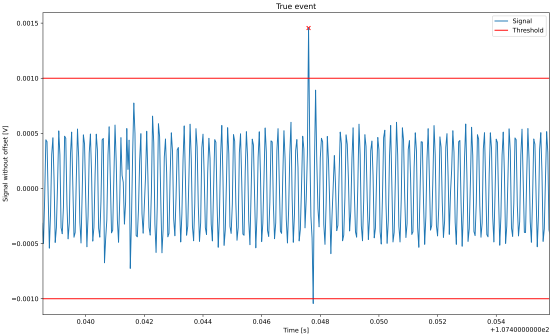
- Quench antennas measure activity along the ramp, all the way to quench, at which point current is extracted from the magnet



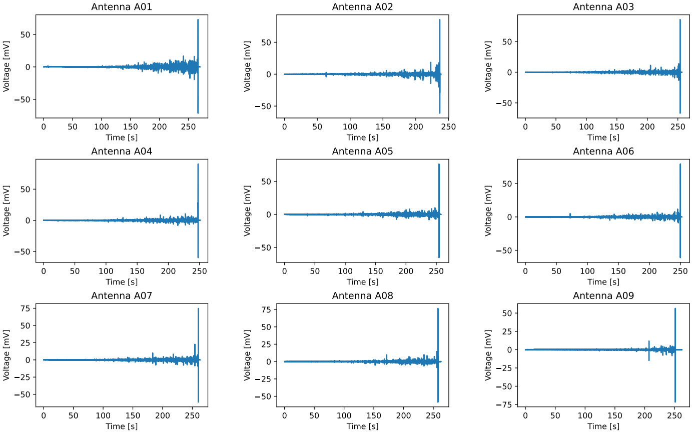
- Voltage spikes along the ramp caused by many possible reasons, some of which are:
    - Current redistribution within the cable
    - Frictional slipping of the cable
    - Vibration of the magnets
    - Epoxy cracks
    - et cetera

Aim of my work

- My job is to analyse 9 different ramps provided by the quench antennas, finding the events prior to the quench, in order to find events that share qualities with the quench
- I then extracted some features from the events, which I then fed to an unsupervised ML clustering algorithm in order to classify the events

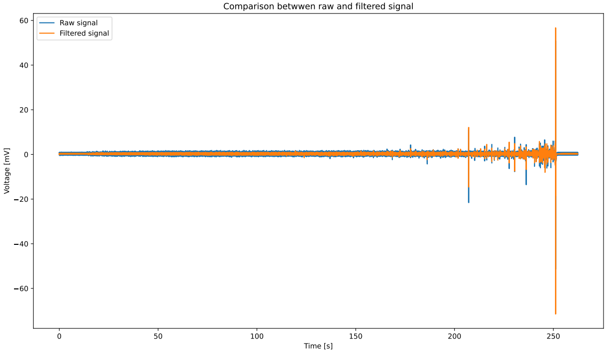


All ramps : plot



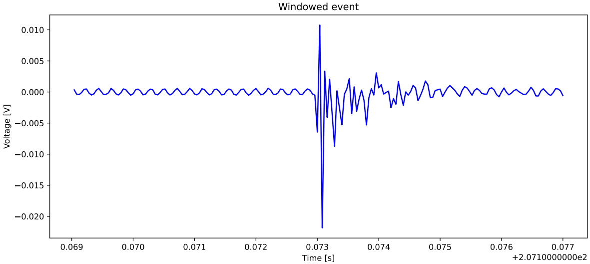
Filter

- To eliminate the background noise ($\nu = 4.54$ kHz), a sixth-order Butterworth bandstop filter was implemented, reducing frequencies in the 4 to 6 kHz range
- From a continuous waveform, trying to build windows around the selected events
- Event selected when we find a peak in the voltage distribution above 1 mV



Features matrix

- Machine learning is not typically done on time series data itself, we need to take this windowed event below and convert it into features
- Features extracted from each event, working only with the filtered signal
- The features were then added to a matrix, which was then fed to an unsupervised clustering algorithm to identify the representative events



Features selected

max	min	norm	int_max	int_min	int_norm	abs_max	int_abs_max
Maximum Voltage	Minimum Voltage	Norm of the voltage array	Maximum value of integrated signal	Minimum value of integrated signal	Norm of the interated signal array	Maximum absolute voltage value	Maximum absolute integrated voltage signal

(continued)

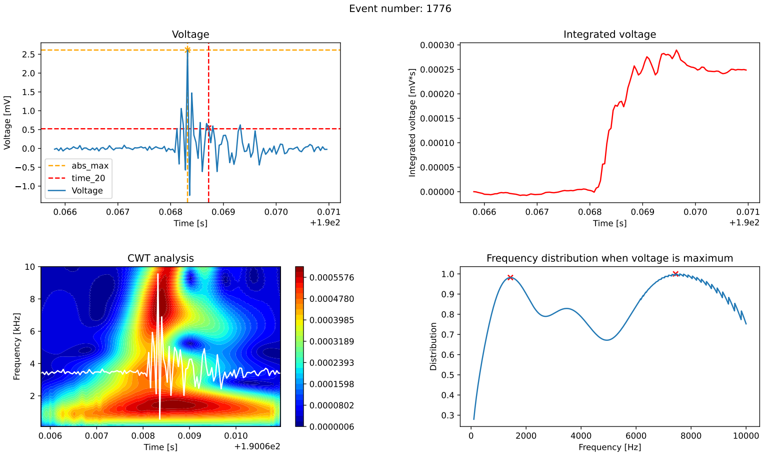
full_int	sec_int	time_80	time_50	time_30	time_20
Definite integral of the signal	Definite integral of the integrated signal	Time between maximum and 80% of the signal	Time between maximum and 50%	Time between maximum and 30%	Time between maximum and 20%

(continued)

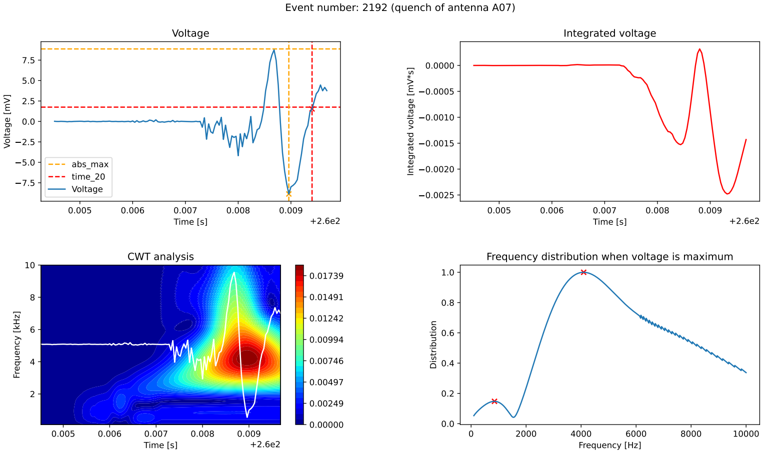
lead_freq	num_peaks	high_peak	std_freq	occ_1000
Highest frequency from the cwt analysis	Number of peaks in the frequency distribution at time when voltage is maximum	Highest peak in the frequency distribution at time when voltage is maximum	Standard deviation of the frequency distribution at time when voltage is maximum	Number of times 1 kHz appears in the frequency distribution at time when voltage is maximum

Figure: Description of the 19 features extracted from each windowed event

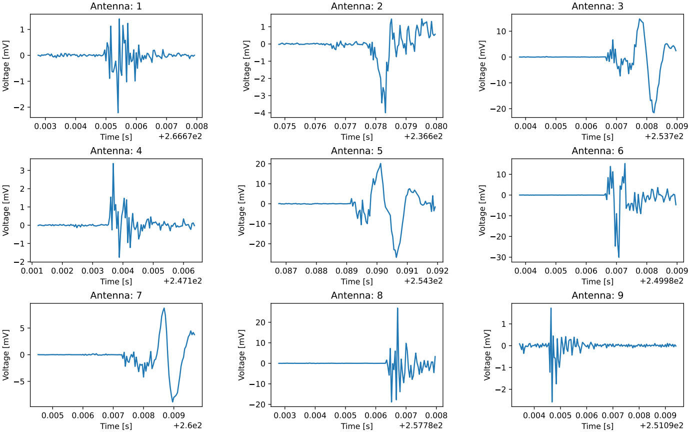
Plots displaying some features



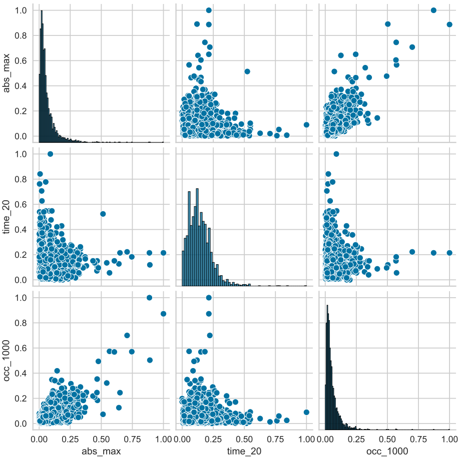
Plots displaying some features: quench event



Quench events



Feature selection for the analysis



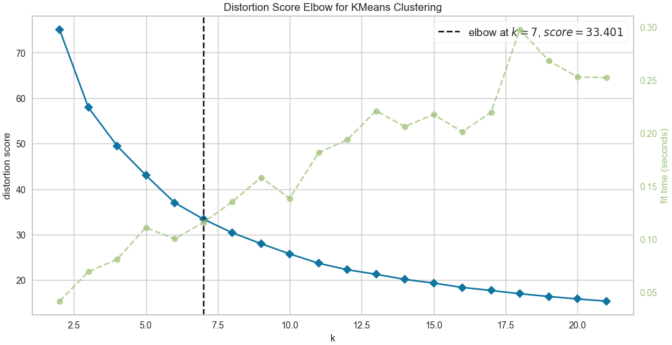
- I decided to work with three features, one for each category:
  - Voltage feature
  - Signal shape feature
  - Frequency feature
- 3 features selected: `abs_max`, `time_20` and `occ_1000`
- Plot on the left shows the correlation between the features
- We note that `occ_1000` and `abs_max` strongly linearly correlated

K-Means analysis

- The Hopkins statistic test gave as a result $H = 0.97$, therefore we are almost certain that the dataset can be clusterized
- *K-means* is a clustering method that aims to partition n observations into k clusters in which each observation belongs to the cluster with the nearest mean
- I started the analysis by finding the optimal value of K, which refers to the number of centroids. I did it using different tests:
  - K-elbow
  - Silhouette
  - Consistency
  - WSS cross validation (Within-cluster sum of squares)

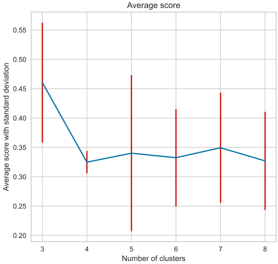
K-elbow analysis

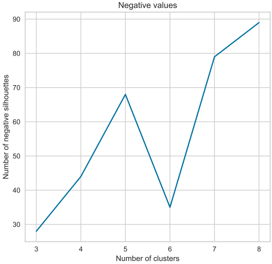
- From the K-elbow analysis we can see that the best value of K is 7, because it is the value in which the slope changes the most



Silhouette analysis

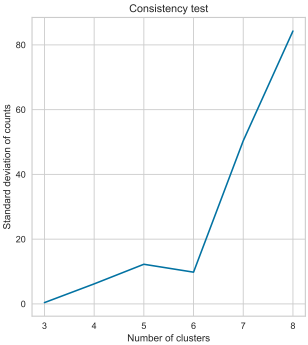
- For the silhouette analysis, I tested the average score (the higher the better, left picture) and the number of negative single silhouette values (the lower the better, right picture). The best value is $K = 3$

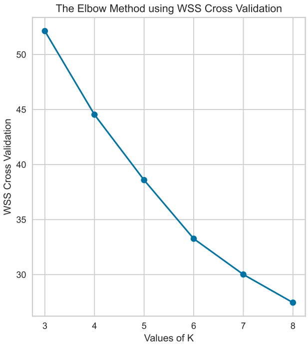




Consistency and cross validation

- From the consistency test we get as best value $K = 3$, because it is the value for which the standard deviation is the lowest
- From the cross validation we get $K = 6$ as best value, because it is the value for which the slope changes the most





Conclusion

- From K-elbow analysis: $K = 7$
- From the silhouette we get:
  - Average score: $K = 3$
  - Negative values: $K = 3$
- From WSS cross validation we get $K = 6$
- From consistency we get $K = 3$

$\Rightarrow$ We have chosen $K = 3$, which suggests that there might be 3 representative types of events happening along the ramp

Silhouette

- Cluster 0: 1510 events (3 quenches)
- Cluster 1: 813 events (0 quenches)
- Cluster 2: 168 events (6 quenches)

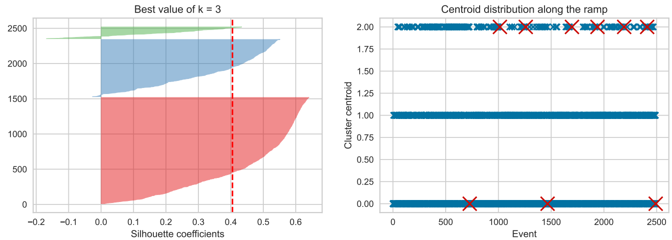
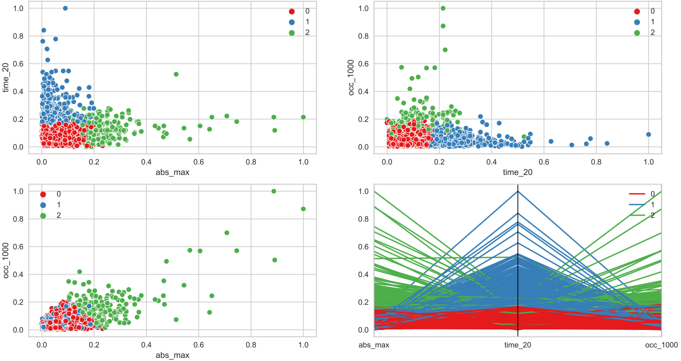


Figure: Silhouette (left) and centroid distribution along the ramp (right), which shows to which cluster each event belong to. Red crosses are the 9 quenches

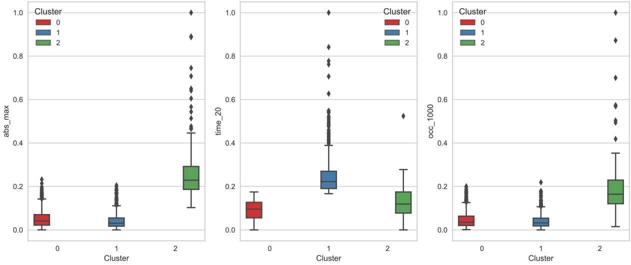
Visualization and Parallel plot

From the parallel plot (bottom right) we can see the trend of the features inside each cluster, and from the other plots we can see where each event is clustered



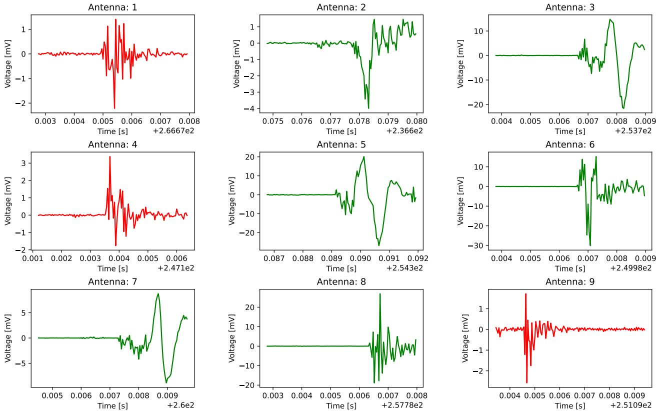
Box plot

- From the box plot we can see what the average values of the elements inside the cluster are
- Cluster with most quenches has a higher value of `abs_max` and `occ_1000`
- Cluster with no quenches has high value of `time_20`



Quenches in clusters

Red: cluster 0, green: cluster 2



Some random events for Cluster 0

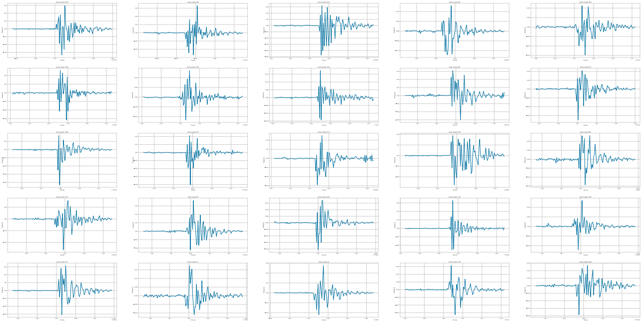


Figure: Events in cluster 0: could be mechanical events

Some random events for Cluster 1

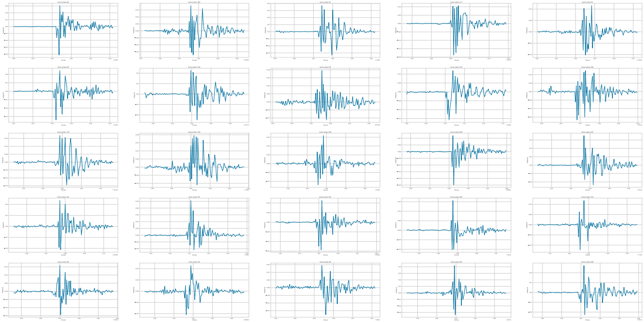


Figure: Events in cluster 1: low amplitude events

Some random events for Cluster 2

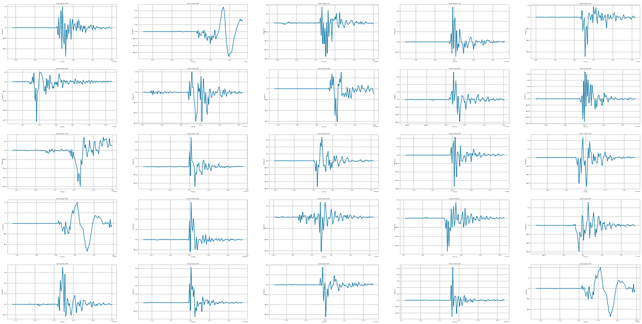


Figure: Events in cluster 2: could show signs of current redistribution, same as quenches

Conclusion and perspectives

- We see some events that look like current redistribution clustered together with the quench
- This events show a 1 kHz oscillation, which is the same oscillation observed in some of the quenches
- Other events clustered together could be mechanical events, because we see a sudden spike followed by a fast decrease
- Cluster 1 (0 quenches) is made mostly of low-amplitude events

Summary and next steps

- Goal: use Machine Learning to identify and learn about the disturbances in high field superconducting accelerator magnets
- Achieved:
  1. Build a routine to automatically extract windowed events from continuous data
  2. Analysis of windowed events for signal characteristics, signal shape and frequency distribution
  3. Perform K-means clustering on data
- Result: current redistribution appears to happen along the ramp, and sometimes it is recovered, whereas other times quench happens
- This result will inform on the performance limits of Nb_3Sn magnets

Thank you for the attention