Determining signal processing strategies to eliminate Flame Detector analogue noise generated by GHz frequency interference

Daniel Sikar - Jupyter Notebook link https://smcse.city.ac.uk/student/aczd097/inm430.html

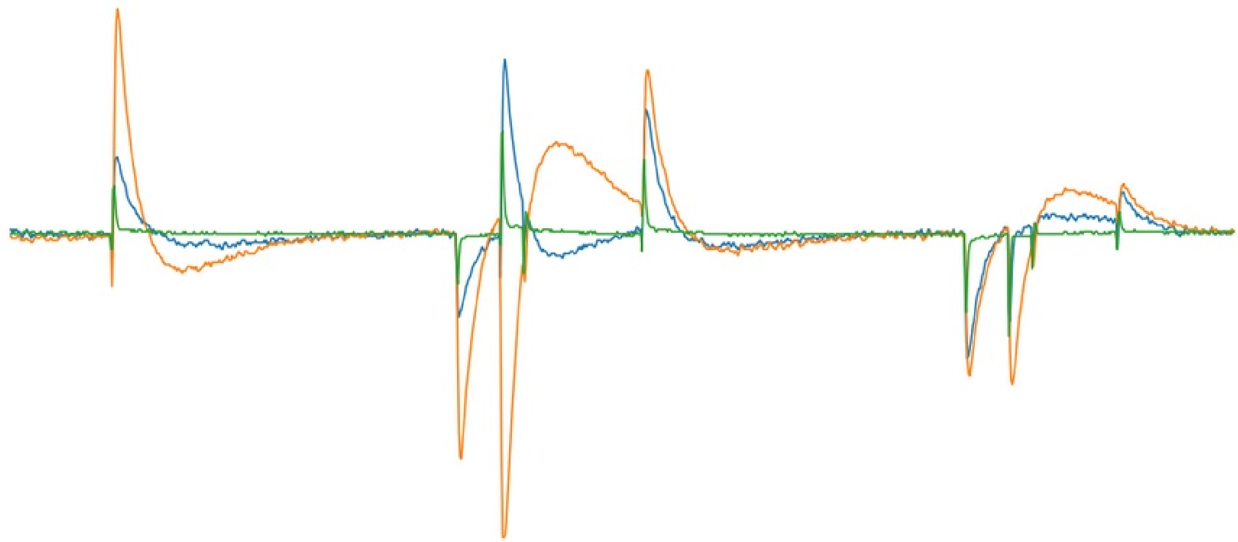

Fig. 1. Analogue signals subject to radio frequency interference

Keywords—Signal processing, analogue noise, gigahertz frequency interference

1 Introduction

1.1 Domain overview

Flame detectors are widely used in areas subject to fire hazards such as oil and gas installations and chemical plants. Detectors consist of hardware and software subject to SIL (Security Integrity Level) certification, aiming and reducing risk effects. Standards such as the IEC 61508 [2] are used to certify equipment and ensure compliance.

1.2 Problems to be tackled

To carry out the analysis the barriers to overcome consist of:

- processing log files
- choosing appropriate libraries
- engineer features to inform our decisions

1.3 Analytical questions

The analytical questions we want to ask is how can signal be differentiated from noise? Though distance functions? Linear regression? A combination of both?

1.4 Objectives

- Trial different techniques
- Find a suitable model to eliminate noise (smoothing algorithm)

  Note, this could be a combination of existing algorithms, to make best use of the attributes present in available dataset.

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1.5 Data source

The data being analysed consists of data logs generated by commercially available flame detectors. Twenty eight files were examined in total, generated under test conditions. One log file (Test45.log) containing real fire data, some of the remaining logs containing RF (radio frequency) data erroneously reported in software as fire - this will be shown in attributes.

The logs files were obtained from a flame detector undergoing Functional Safety of Electrical/Electronic/Programmable Electronic Safety-related Systems, as defined in the IEC 61508 standard [2]. One log file (Test45.log) containing real fire data, the other logs, some containing RF (radio frequency) data erroneously reported in software as fire.

1.6 Analysis strategy

Once our signal and noise have been characterized, our analysis strategy consists of engineering features, as well as creating models to quantify the levels of noise and signal. Distance functions, fft transforms and filters, such as proposed by Savitzky and Golay [1] provide a scheme to smooth signals, eliminating noise. In this work, we shall examine such schemes and compare the end results, determining by sch observations a filtering strategy to eliminate noise generated by GHz frequency interference.

2 Discussion

We processed our data by transforming hexadecimal encoded byte values into numerical valued between 0 and 255 (unsigned bytes) as well as all the bit flags present in our flame detector units under test. We isolated two files (Test45.log, Test48.log) and a further representative section within these files, representing signal (fire) and noise (interference). Both sets of data plotted as Flame A detector, Flame B detector and Guard as discussed in Jupyter Notebook.

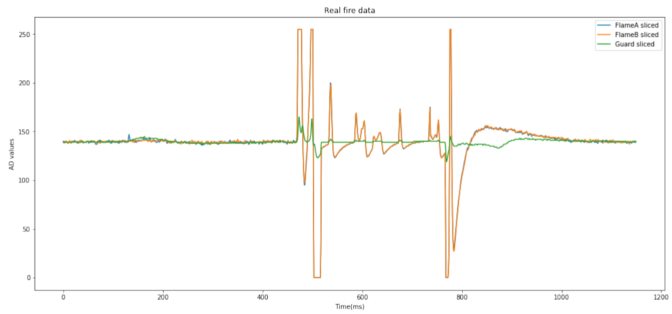

Fig. 2. Closely overlapping Flame A and Flame B fire data

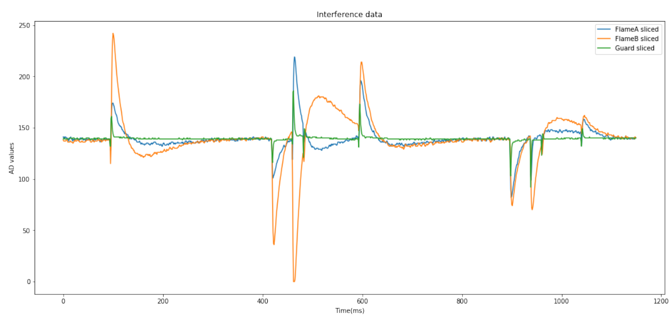

Fig. 3. Interference plot, Flame A and Flame B with little or no overlap

2.1 Signal data

We plotted our signal data finding that the fire event generated values for Flame Detector A and Flame detector B that closely overlapped.

2.2 Noise data

We plotted the same section of our noise data and found that Flame A and Flame B did not overlapped, in fact in parts they were going in opposite directions (antiphase), finding that this could become an engineered feature.

2.3 Data normalisation

We normalised our data, initially using a per-attribute minimum and maximum values:

$$z_i = \frac{x_i - min(x)}{max(x) - min(x)}, max(x) - min(x) \neq 0$$

And found that this approach distorted our plot.

So we modified the normalisation algorithm using minimum and maximum values across all attributes as they are scaled to same values (0-255)

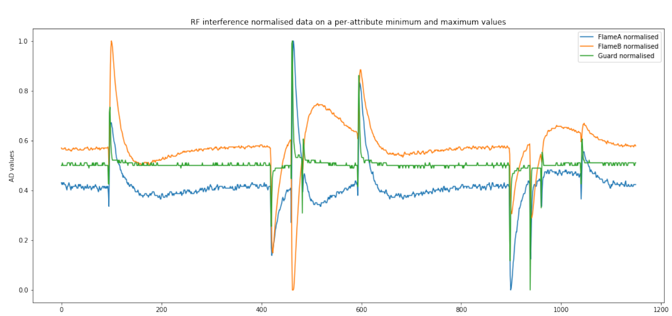

Fig. 4. Normalised plot with distortion, per attribute minimum and maximum values

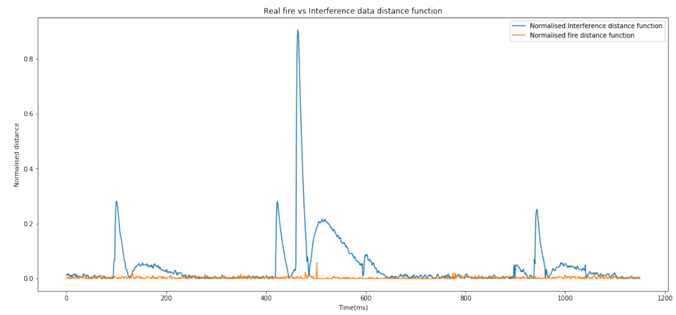

Fig. 5. Fire and interference distance function

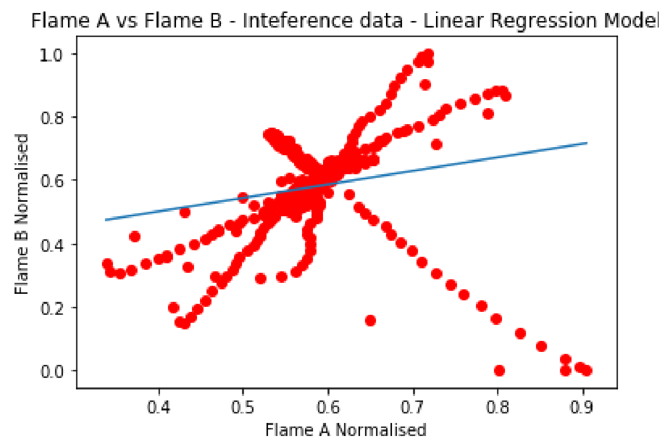

Fig. 6. Interference linear regression - weak positive correlation

$$z_i = \frac{x_i - min}{max - min}, max - min \neq 0$$

2.4 Distance function

Once our data was normalised, we created a distance function expecting that this would provide a measure to distinguish noise from signal. This approach was based on the degree of overlapping presented by Flame A and Flame B signals for fire data and inteference data. we obtained the distance value by the absolute difference of Flame A and Flame B

$$Fd = |Nfa - Nfb|$$

With this engineered attribute we plotted both features to find that interference data presented, as expected, greater distances and fire data.

2.5 Linear regression

Since the distance function showed how closely the signals of Flame A and Flame B were match, we figured it would be a good idea to plot our data plus a line of best fit, to confirm our findings using a well established approach. The interference data proved to have a weak positive correlation, while the fire data proved to have a strong positive correlation.

2.6 Antiphase

Our second and last engineered function was the antiphase flag, that is true whenever Flame A and Flame B signals are moving in opposite directions. This can be determined by dividing the deltas and verifying the sign, if it is found to be negative, the signals are in antiphase.

$$A \Rightarrow \frac{\Delta Fa}{\Delta Fb} < 0$$

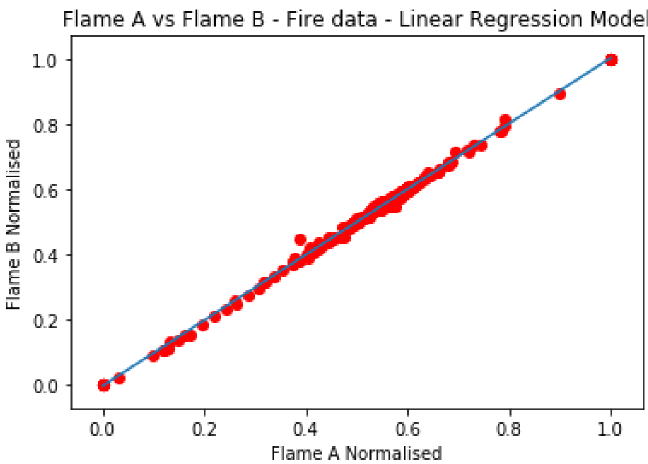

Fig. 7. Fire data linear regression - strong positive correlation

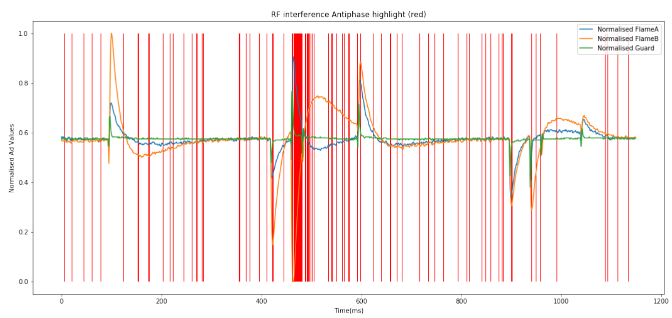

Fig. 8. Interference antiphase highlight (red)

where

$$\Delta Fa = Fa_i - Fa_{i-1}, \Delta Fb = Fb_i - Fb_{i-1}, \forall i > 1$$

With the antiphase attribute we were able to overlay this new attribute with the original plots. This showed us that interference data showed antiphase signals throughout the plot while fire data showed no antiphase in the fire signal section, suggesting that Flame A and Flame B were tightly overlapped.

We did notice however that the antiphase flag was not set throughout signals that visually appeared to be moving in opposite directions, this suggested there is further scope for improvement in the antiphase algorithm, perhaps using a window as in an interval of values, instead of discreet values, and this could be carried out in future works.

Between our distance function and antiphase function, we believe there is enough data to safely distinguish signal and noise which would have commercial applications in ensuring equipment would pass security integrity level approval tests.

Fig. 9. Fire antiphase highlight (red)

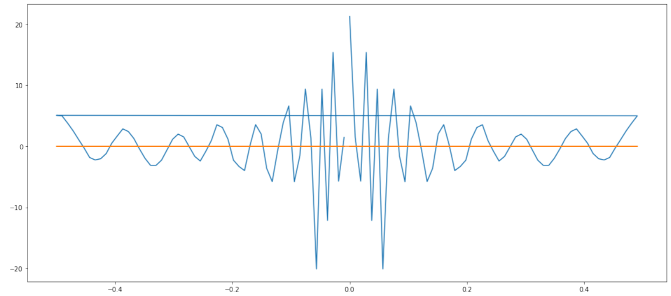

Fig. 10. Interference slice smoothed fast fourier transform

In addition to our engineer attributes, we also attempted fast fourier transforms which did not provide clear pointers, in this instance, as to the usefulness of the approach.

We first transformed noisy data obtaining a frequency plot, then replotted with data smoothed using the Savistzky-Golay filter, and found the frequency showed more regularity, by the increased number of zero crossing observed.

We then plotted the data with no filter applied, which showed a slightly noisier signal as expected, then the same data with a filter applied with is slightly smoother.

Acknowledgments

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References

[1] A. Savitzky and M. J. E. Golay. Smoothing and differentiation of data by simplified least squares procedures. *Analytical Chemistry*, 36(8):1627–1639, Jul 1964. doi: 10.1021/ac60214a047

[2] Wikipedia contributors. Iec 61508, 2018. [Online; accessed 02-December-2018].