Application Notes

Sample Flame Detection Ratio Based Algorithm

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DOCUMENT HISTORY

Version	Date	Change Ref.	Change Details
01	22 JUN 2020	N/A	First Release

1 INTRODUCTION – OPTICAL IR FLAME SENSING CONCEPT

Optical based flame sensing systems that use infrared radiation work by comparing the energy levels within certain ranges of wavelengths of light. This involves a sensor used to give good signal strength for human infrared emissions, a sensor used to detect sunlight effects (and other industrial sources of IR) and a sensor used to detect the emissions associated with hot CO_2 created during a fire.

The three sensors used have interference filters that allow a limited range of wavelengths to transmit through the material and increase the temperature of the pyroelectric element. These filters have a central wavelength of transmission and a pass band either side. As an example the SMD Flame Sensing Evaluation Kit USEQFSK1000000 includes four sensors whose wavelength ranges are:

USEQFSEA50L180 = 5.0 μm long pass (anything over 5.0 μm wavelengths)

USEQFSEA391180 = 3.91 μm with 90 nm bandpass (3.91 μm ± 45 nm)

USEQFSEA464180 = 4.64 μm with 180 nm bandpass

USEQFSEA448180 = 4.48 μm with 620 nm bandpass (4.48 μm ± 310 nm)

As well as considering the magnitude of emissions within certain ranges of wavelengths, another concept involved in optical based IR flame sensing is the frequencies of magnitude variation in these wavelength ranges. The reason that this is important is that a fire is not a static phenomenon. Due to this it is important to characterise the energy levels of light incident on each sensor by focusing on variations in the frequencies of the output signals of the sensor. This is accomplished by first putting the raw data through a high and low pass filter to cut out frequencies that are not associated with the dynamics of fire. In general a good range to capture them is between 1 and 30 Hz. This is a large generalization and every circumstance may produce different results, for example a forest fire will produce different results to a small indoor fire. However the specific frequency ranges need to be determined through testing in order to reduce the range of frequencies being analysed for the specific application that a system is being designed to work in.

If the signal strength within these range of frequencies is largest on the flame sensor (4.48 μm ± 310 nm) then a fire can be determined to be in the field of view of the flame sensing system with a reasonable certainty.

2 A DESCRIPTION OF A FLAME SENSING ALGORITHM

The flame algorithm that is in use on the SMD Flame Sensing Evaluation Kit USEQFSK1000000 uses the magnitude of the FFT plots of each of the sensors. Each sensor has the same data processing applied to it prior to the ratio based comparison.

Key equations for understanding the usage of FFT calculations.

1. $Highest\ Detectable\ Frequency = Nyquist\ Frequency = \frac{Sample\ Frequency}{2}$

This is important to ensure that the sample frequency is set high enough to observe the highest frequency that you are interested in.

2. $Number\ of\ FFT\ Bins = \frac{FFT\ Window\ Width}{2}$

This is used to determine the resolution of the FFT in equation 3.

3. $Resolution\ of\ Bins = \frac{Nyquist\ Frequency}{Number\ of\ FFT\ Bins}$

The resolution is important for the situation where you want to ignore the bins that have leakage from the DC bin. If you want to accurately observe the frequency at 1 Hz then you must ensure that the resolution allows for this frequency to be monitored without incorporating the bins that DC components have affected due to spectral leakage of the FFT. This is easily visualized by changing the window width in the KEMET Flame Sensing Evaluation Tool Software whilst viewing the FFT plots of each channel. Larger window widths allow for better resolution.

An FFT bin is the name given to grouping a range of frequencies into a single value centred at a particular frequency. Increasing the number of FFT bins means that the number of frequencies being grouped together is smaller and a larger number of bins will comprise the same frequency range. Please see section 9 for a visual aid to understanding FFT bin resolution.

4. $Time\ Period\ of\ Window = FFT\ Window\ Width\ \times Sample\ Period$

The time period of the window being analysed is important when considering the response time of the algorithm. The longer the window the longer the algorithm takes to respond. It is a trade-off between response time and stability.

The data processing prior to the comparison is comprised of 5 steps described in section 3.

3 INITIAL SENSOR DATA PROCESSING

3.1 FFT Window Width

This is the window of data that is being used by the FFT. It can be visualized by a plot of data containing exactly the number of data points set by the parameter FFT Window width.

The image below shows a window of data 1,024 points long.

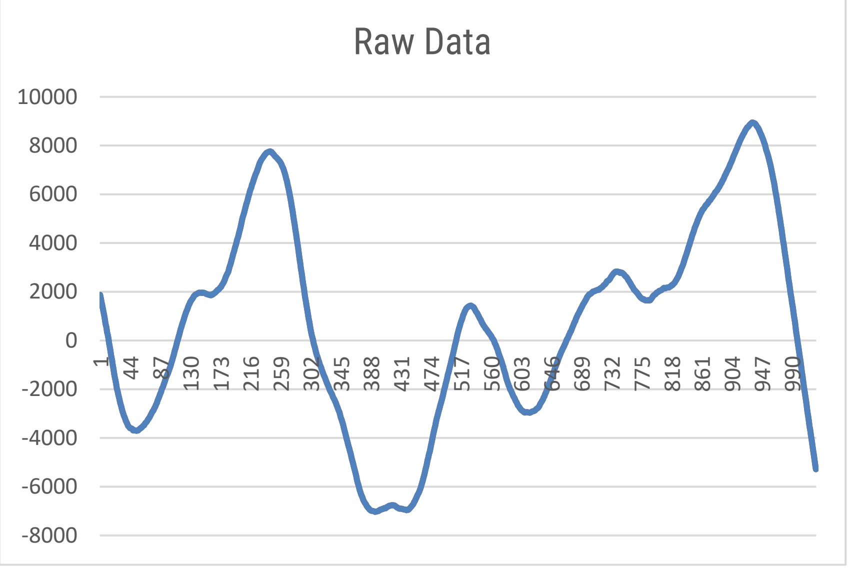


Figure 1 – Raw Fire Data

3.2 Hanning Window

The Hanning Window is used as it reduces an aspect of the FFT calculation known as spectral leakage. The Hanning Window is a data set of the same length as raw data set.

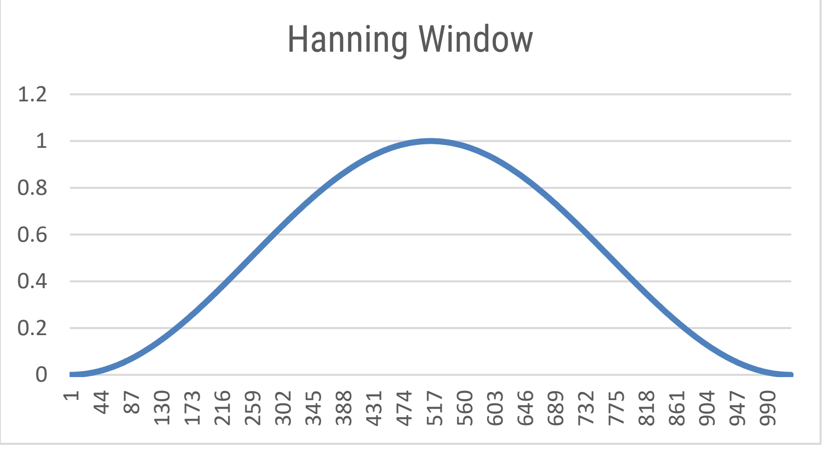


Figure 1 – 1,024 Points Hanning Window

The equation for producing each element, ‘n’, of a Hanning Window for a data set ‘N’ elements long is

$$w(n) = sin^2\left(\frac{\pi n}{N-1}\right)$$

The Hanning Window data set is then multiplied by the FFT window raw data element by element

$$Hanned\ Data\ Window[i] = Hanning\ Window[i] \times Raw\ Data\ Window[i]$$

This forces the ends of the data set to zero in a smooth manner.

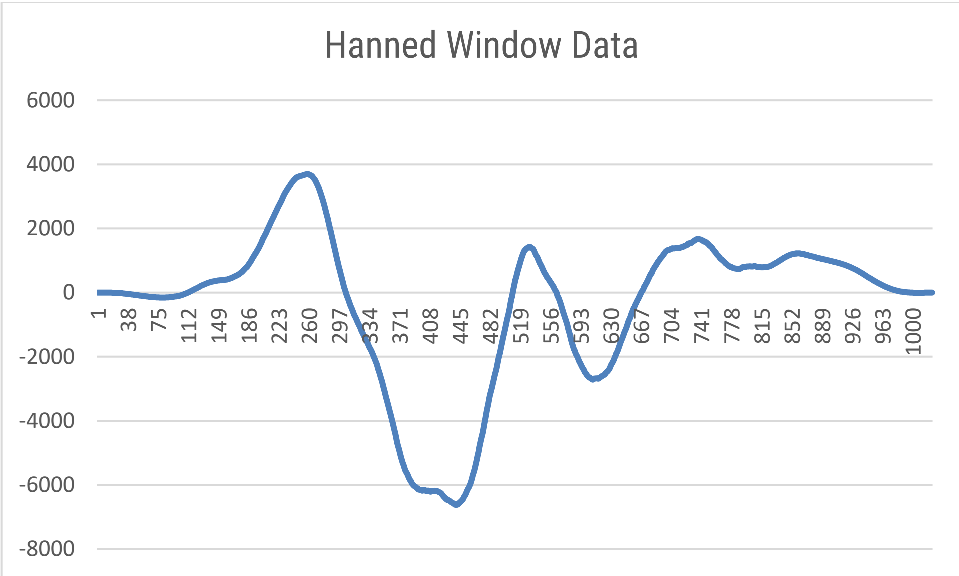


Figure 2 – Hanning Window Modified Data Set

3.3 FFT

The data at this stage has been prepared for the FFT function to be performed. The output of an FFT can be visualised well using a bar plot. An example of FFT bar plot is shown below.

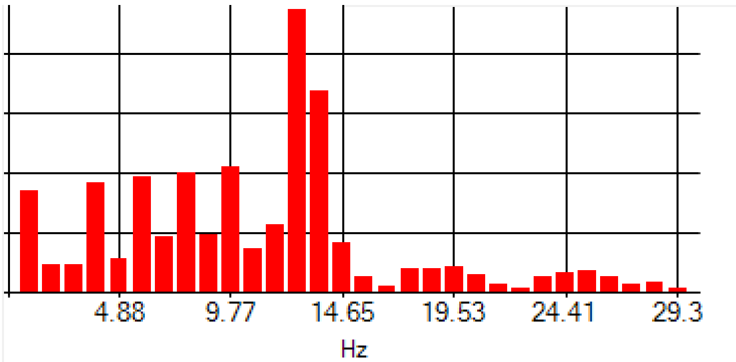


Figure 3 – FFT Plot Using 1,024 Window Width

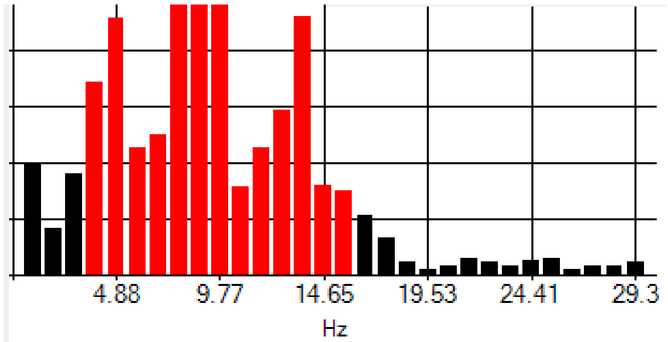
This provides a data set corresponding to the signal strength for each frequency able to be determined based on the set up of the algorithm.

3.4 FFT Summation

Now that the frequencies are available in the FFT dataset this stage involves looking at the desired frequency range. This is done simply by summing the values of the bins between the desired low and high frequencies.

$$Channel_x\ Signal\ Strength = \sum_{Low\ Freq}^{High\ Freq} FFT\ Dataset$$

For example using the range of 4 and 16 Hz would add all the values of the following graph that are in red and ignore anything outside this range.



By doing the above summation we now have a single value that represents the signal strength of a particular sensor in the range of frequencies set by the algorithm parameters.

3.5 Signal Multiplier

This next stage allows for further calibration of the system. It is simply a means to reduce or increase the value produced by the summation performed previously. This allows for compensation of differences in responsivity and noise levels of the sensors used in the system.

$$\mu_x(Channel_x\ Signal\ Strength) = \mu_x\left(\sum_{Low\ Freq}^{High\ Freq} FFT\ Dataset\right)$$

The effect of μ_x is shown below, it is simply multiplication.

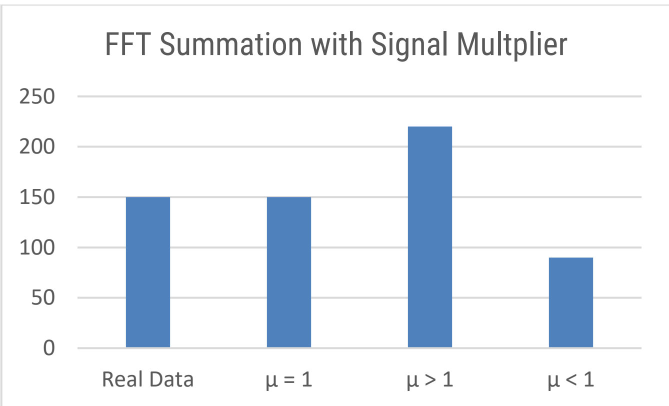


Figure 4 – Signal Multiplier Effect

3.6 Summary of Data Processing

The previous sections describe the stages required to process the data when doing an FFT based flame sensing algorithm.

1. Get a full window of data corresponding to the FFT window width that you have selected.
2. Multiply element by element to produce a data set that converges to zero at either end.
3. Perform the FFT on the data set produced from raw data and Hanning window.
4. Sum the value of the FFT bins in the desired frequency range.
5. Apply a single multiplier if needed to compensate for any system level differences.

The flow of this is as shown below.

The outcome of the above stages results in a data point for each sensor which for the next section will be labelled according to the flame Evaluation kit channels. The labels specific to this user case are listed below.

1. $\varepsilon_1 = Ch1\ Human\ Motion\ Rejection\ (5.0\ um\ LP) = \mu_1 \times \sum_{Low\ Freq}^{High\ Freq}(FFT\ HM)$

2. $\varepsilon_2 = Ch2\ Sunlight\ Rejection\ (3.91\ um\ BP) = \mu_2 \times \sum_{Low\ Freq}^{High\ Freq}(FFT\ SR)$

3. $\sigma_1 = Ch3\ Flame\ Channel\ 1\ (4.48\ um\ BP) = \mu_3 \times \sum_{Low\ Freq}^{High\ Freq}(FFT\ F_1)$

4. $\sigma_2 = Ch4\ Flame\ Channel\ 1\ (4.64\ um\ BP) = \mu_4 \times \sum_{Low\ Freq}^{High\ Freq}(FFT\ F_2)$

Epsilon 1 and 2 (ε_1, ε_2) represent the rejection channels after the data processing listed in this section and sigma 1 and 2 (σ_1, σ_2) represent the flame channels output for the data processing listed above.

With these it is now possible to check the ratio of the post processed flame channels against the rejection channels. This is described in the next two sections.

4 RATIO BASED ALGORITHM

Since the algorithm is based on the ratio of the flame channels to rejections channels post processed values we need to select our ratio which if met will produce a fire detection result. This comes down to setting up the values. The values will differ from system to system but can be adjusted to take system differences into account. Here the example ratio used is 1.5

$$Human\ Motion\ Rejection\ Ratio\ Threshold\ =\ 1.5 = \frac{\sigma_1}{\varepsilon_1}$$

or

$$Human\ Motion\ Rejection\ Ratio\ Threshold\ =\ 1.5 = \frac{\sigma_2}{\varepsilon_1}$$

This means that at least one of the flame channels must produce an output signal after the processing described in section 3 that is at least 1.5 times the rejection channel. It is the same for the sunlight rejection channel. Here the example ratio used is 1.2

$$Sunlight\ Rejection\ Ratio\ Threshold\ =\ 1.2 = \frac{\sigma_1}{\varepsilon_2}$$

or

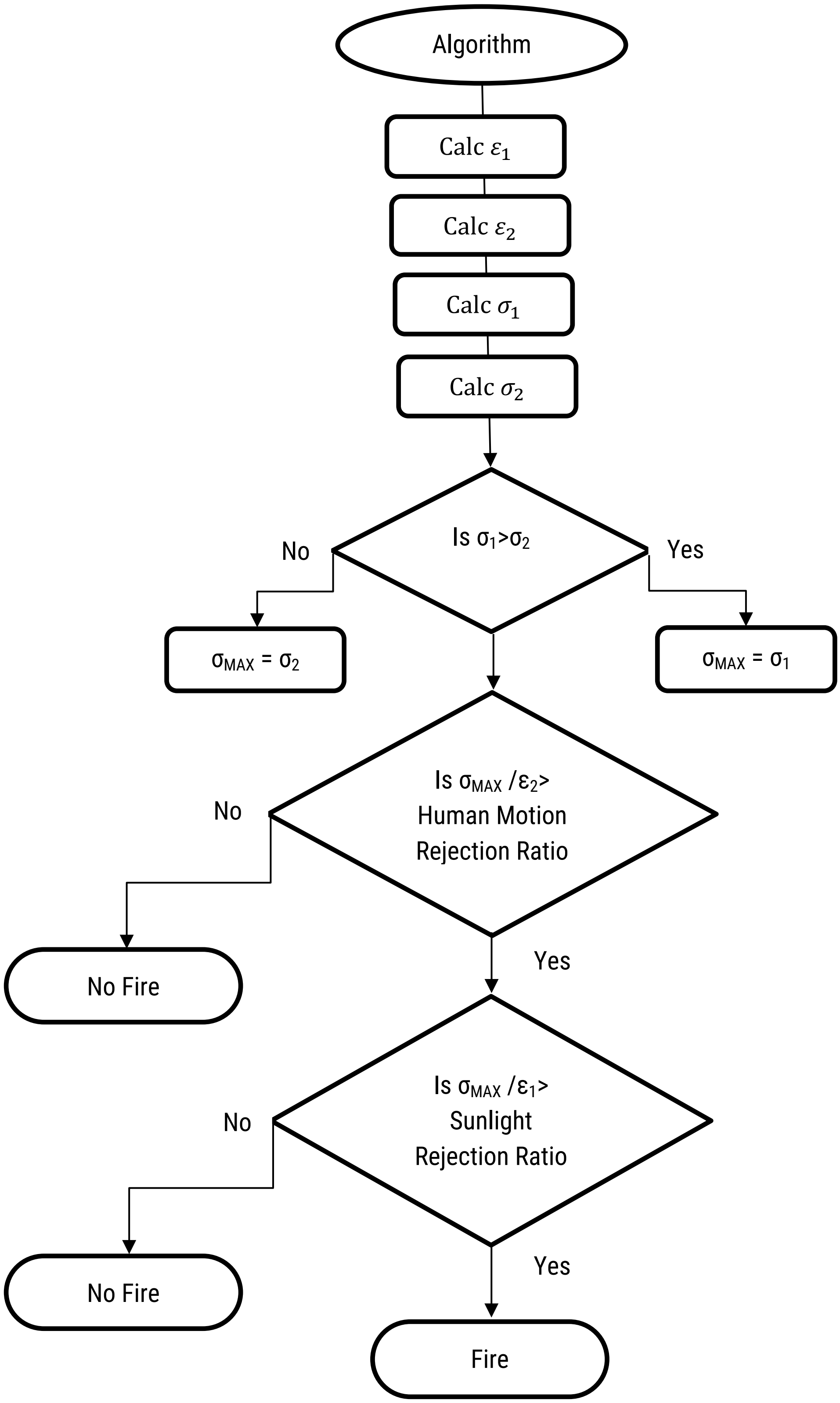
$$Sunlight\ Rejection\ Ratio\ Threshold\ =\ 1.2 = \frac{\sigma_2}{\varepsilon_2}$$

For a flame event to be considered real, one of the flame sensors data must be greater than the ratios of both of the two rejection channels.

Since one of the flame channels will be larger than the other it is only required to look at the ratios of the largest flame channel signal against the rejections.

This is shown in the flowchart in the next section.

5 FLOWCHART


Algorithm
Calc ε_1
Calc ε_2
Calc σ_1
Calc σ_2
Is $\sigma_1 > \sigma_2$
No
Yes
$\sigma_{MAX} = \sigma_2$
$\sigma_{MAX} = \sigma_1$
Is $\sigma_{MAX} / \varepsilon_2 >$
Human Motion
Rejection Ratio
No
No Fire
Yes
Is $\sigma_{MAX} / \varepsilon_1 >$
Sunlight
Rejection Ratio
No
No Fire
Yes
Fire

6 SUMMARY

The key points are listed below.

1. Perform post processing as described in section 3.
2. Determine largest flame channel signal.
3. Divide the flame signal by rejection channel 1. If greater than that channel's threshold check other channel.
4. Divide the flame signal by rejection channel 2. If greater than that channel's threshold a flame event has been registered.

7 ENHANCEMENTS

The final part of the flow diagram can be replaced with a counter. The counter would store some number of fire or no fire events. When the ratio of fire to no fire events reaches some proportion of the total number of recorded events then a fire can be said to be in the field of view of the sensors. This makes the system less responsive but more robust against short time duration events that could cause a false alarm.

8 MCU BASED ALGORITHM

Due to the computational expense of the FFT, especially on larger window sizes, it may be desirable to not use FFT calculation on a microcontroller.

It is extremely useful to view the data in such a way as it shows you the actual frequencies that you should be interested in. For initial testing with the SMD Flame Sensing Evaluation Kit USEQFSK1000000, this is very desirable.

Most system designers use a computationally less expensive form of the same type of processing explained in this document.

1. High and low pass filter, implemented in op-amps when using an analogue sensor. When using a digital product the same effect can be accomplished with digital signal processing.

At this stage the signal still contains the frequencies you are interested in as set by the filters being used. However if the SMD Flame Sensing Evaluation Kit USEQFSK1000000 used this method you might not see other frequencies that you could use in your algorithm.

2. Perform RMS on a window of data to determine the signal strength of the combination of the frequencies in the bandpass of the filters used.

This is equivalent to being at the beginning of stage 5 of the data processing described in this document prior to applying the signal multipliers.

Raw Data → High and Low Pass Filters → RMS on Window of Data → Apply Signal Multiplier

The window of data in the 3rd box has the same effect as increasing the FFT window width in terms of the time response to an input signal. Longer windows are more stable but slower to respond. This can be set to any value desired as it does not have the restriction of being value of the form 2^x like the FFT.

After the signal multipliers the same comparisons can be performed as written in sections 4 and 5.

9 FFT BINS

The easiest way to visualise the effect of increased resolution of the FFT is to show the plot of the FFTs produced from our sensors. Increased resolution of the FFT means that there are a larger number of FFT bins within the same range of frequencies.

For a sample frequency of 1 kHz (highest sensor sampling frequency) and plotting the FFTs within 0 to 30 Hz using the KEMET Flame Sensing Evaluation Tool Software shows the increased number of bins as the window width is increased. The frequency range being included by the algorithm has been left as 4 to 16 Hz for all the diagrams. As can be seen in Figure 6 the range of 4 to 16 Hz includes the first bin that will contain leakage from the DC bin. This is generally undesirable.

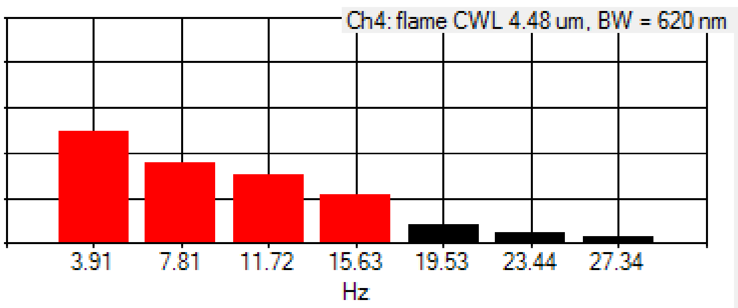


Figure 5 – FFT Window Width = 256

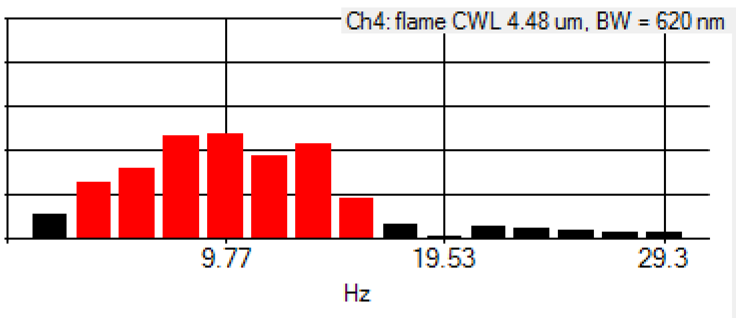


Figure 6 – FFT Window Width = 512

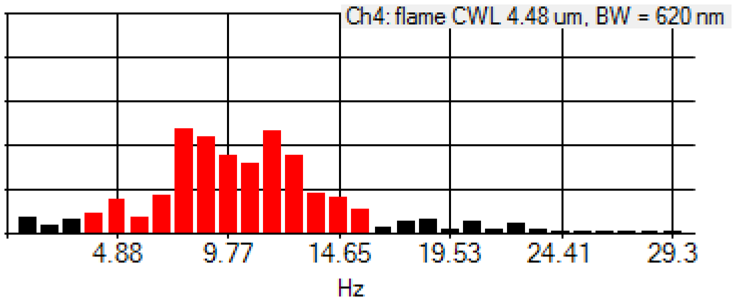


Figure 7 – FFT Window Width = 1,024

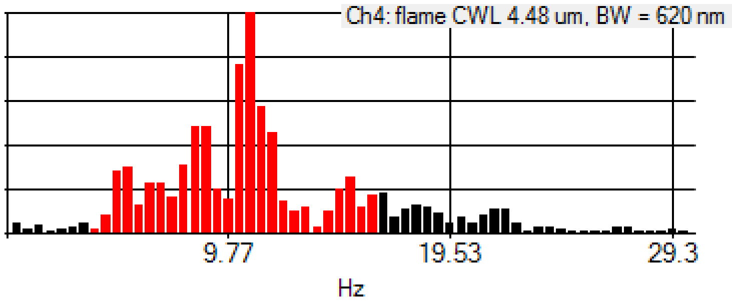


Figure 8 – FFT Window Width = 2,048

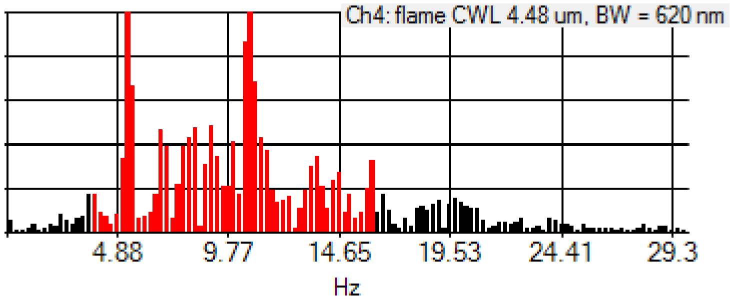


Figure 9 – FFT Window Width = 4,096

As can be seen the number of bins within the range 0 to 30 Hz increases as the window of data being analysed is increased.

Increasing the resolution in this way allows the user to be more selective of the cut-off frequencies but longer windows of data are slower to respond to new events. This is a compromise that needs to be determined through testing for a specific application.

Summary

1. FFT window width should be large enough to allow the user to select the frequency range desired accurately.
2. FFT window width should be large enough to give a resolution that allows the bins susceptible to DC bin leakage to be ignored by the algorithm.
3. FFT window width should not be too large to introduce undesired time delays associated with large windows of data to show significant response to input signals.