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| **Student Name:** | **Aaron Dinesh** |
| **Student ID Number:** | **20332661** |
| **Assessment Title:** | **DSP Lab 04** |
| **Lecturer (s):** | **Naomi Harte** |
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I hereby declare that this assessment submission is entirely my own work and that it has not been submitted as an exercise for a degree at this or any other university.

I hereby declare that I have not shared any part of this submission with any other student or person.

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I am aware that the module coordinator reserves the right to submit my exam to Turnitin and may follow up with further actions if required should I be found to have breached College policy on plagiarism

**A drawing of a person's head

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**Signed:**

DSP Lab 04

# Ex 1.1.1

Here I create some code to generate note 69 and plot the corresponding frequency components in an FFT plot shown below. The frequency contained in the signal is evident by the large spike at 440Hz. Since the FFT is symmetrical about the y-axis, I will be limiting the FFT graph to positive frequencies for better clarity.

A graph of a graph

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Figure 1 - FFT plot of note 69.

We were then asked to generate note 110 and try to plot the frequency components of that signal. When calculating what the frequency should be we get a value of:

By the Nyquist-Shannon Sampling theorem we know that we can’t perfectly capture this signal without introducing aliasing in the form of new frequency components. We know that this frequency component will lie at:

When we plot the FFT of the signal we see this aliased frequency appearing. With the current sampling rate the max note we would be able to show would be note 107.

A white screen with numbers and lines

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Figure 2 - FFT plot of note 110 with aliased frequency.

# Ex 1.1.2

Here I chose notes 48 to 51, each with a 1 second duration. The sampling rate remained unchanged. Shown below is the FFT plot for those 4 notes, showing that we can still resolve these notes (4 distinct peaks) even though they are consecutive.

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Figure 3 - FFT plot of 4 consecuitve notes. 4 distinct peaks show that we can still resolve these notes

# Ex 1.2.1

Here I created an audio signal that had two notes playing simultaneously. The frequencies can be seen in the FFT plot below:

A graph of a graph

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Figure 4 - FFT Plot of notes 48 and 90

I created two ideal filters, one lowpass filter with a cutoff of 140Hz and a highpass filter with a cutoff of 1000Hz to isolate both notes on their own. After filtering both the signals, I plotted their FFTs below:

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Figure 5 - FFT of lowpass filtered signal.

A screen shot of a computer

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Figure 6 - FFT of highpass filtered signal

As shown in the FFT graphs above the lowpass and highpass filters perfectly isolated the two notes.

# Ex 1.2.2

For the signal x1 I created a vector of notes from 50-71 in steps of 1. They all started at the same time and last for 1 second. The DFT of x1 is shown below:

A graph of a graph

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Figure - DFT plot of x1.

For x2 I created a vector of notes ranging from 72 to 90, in steps of 1. I had them all start at the same time and last for a duration of 1 second. The FFT of x2 is shown below.

A graph of a graph

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Figure - FFT plot of x2.

I created the signal x by summing signals x1 and x2 together, which gave me the resulting FFT plot:

A graph of a graph

Description automatically generated with medium confidence

Figure - FFT plot of x

From examining the 3 FFT plots I determined that a filter with a 500Hz cutoff should be sufficient to recover x1 and x2 from x. I also computed the Euclidian distance between the originals and recovered signals and found the distance to be 17.0826 for x1 and x2. Shown below are the FFT plots for the original and recovered signal.

A group of graphs showing different types of data

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Figure - FFT plots of original and recovered signal

I also tested a range of cutoff frequencies and plotted their results to determine the best cutoff frequency to use (corresponding to minimum Euclidian distance). The result of this test is displayed in the graph below.

A screen shot of a graph

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Figure - Graph of Euclidian Distance (minimum point shown)

From this plot I deduced that the optimum cutoff frequency would be 498Hz.

Based on the work done before I also created a bandpass filter to isolate just the melody from the “melody2.wav” file. Through experimentation I discovered that the optimum filter was a bandpass filter with cutoff frequencies at 349Hz and 786Hz. The result of this filtering is saved to a file titled “filteredMelody2.wav”.

A graph of a graph

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A screen shot of a graph

Description automatically generated

Figure - FFT Plots of original and filtered melody2.wav

# Ex 1.3.1.1

A blue and yellow graph

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Figure - Spectrogram of Piano Note C5

A blue and yellow grid

Description automatically generated

Figure - Spectrogram of Flute Note C5

A green and yellow lines

Description automatically generated

Figure - Spectrogram of Trumpet Note C5

A blue and yellow striped pattern

Description automatically generated

Figure - Spectrogram of Violin Note C5

Plotted above is the spectrogram (40ms window length) of 4 different instruments playing the same note C5 which is around 523Hz. In all the spectrograms we can see a strong fundamental frequency at 523Hz. It is this fundamental frequency that we perceive as being the note C5, while the various harmonics give the instrument its characteristic sound.

When looking at the piano we can see the fundamental frequency and 8 harmonics. The decay of the harmonics seems to be related to its frequency with higher frequency harmonics fading away faster. We also see a strong spike across all frequency components at the beginning where the hammer hits the string in the piano. This sudden motion from rest is also what gives rise to the upper harmonics. Once the sudden impulse is gone, the string will eventually vibrate at its fundamental frequency. This high frequency harmonic decay can also be heard in the “piano-C5.wav” file. The piano note starts off high pitched and we can hear it decay to what 523Hz should be.

The flute spectrogram tells a similar story, we see the fundamental frequency centred around 523Hz with 8 visible harmonics. Although when compared to the piano we don’t see the same harmonic decay in time. This makes sense when considering that the musician has to constantly blow to make the note, as opposed to the hammer action in a piano. As such there is no time for the harmonics to decay. Also, it is interesting to note the sinusoidal like oscillations at each frequency component. This can also be evidently heard when listening to “flute-C5.wav”. I believe this vibrato is an artistic choice by the flutist rather than a characteristic of the instrument itself, since these oscillations don’t appear on the trumpet spectrogram even though both these instruments work using similar principles. Such effects like these are only limited to wind instruments since they rely on the musician blowing air through the instrument to produce the notes. Musicians change the way they deliver this air to produce different effects. It is these effects and the constant power in the harmonics that give the flute it’s rich sound.

Looking at the trumpet we see a similar story as the flute. However, while the flute had decaying power in the harmonics in the frequency domain, we see that the trumpet has the same power across all the harmonics in the frequency domain. Since this is also a wind instrument, we don’t see the decay in the power of the harmonics in the time domain either. Since all these harmonics are expressed strongly in the note, it leads to a sound that is incredibly rich. We also don’t see the sinusoidal oscillations in the spectrogram which is backed up by the lack of vibrato when listening to the “trumpet-C5.wav”.

The final sound we had to analyse was the “violin-C5.wav”. When looking at the spectrogram of the violin we see 9 distinct overtones with decreasing power in the frequency domain. It is interesting to note as well the large power in the first 7 overtones. This is in stark contrast to instruments like the flute or the piano which had a lot lower power in its harmonics. Again contributing to a richer sound when compared to the piano or the flute. We can also see the vibrato in the notes, as the bow is being pulled across the strings. This is down to an artistic expression by the violinist.

# Ex 1.3.1.2

A blue and green line graph

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Figure - Spectrogram of Piano C5 Note

A blue and yellow line graph

Description automatically generated

Figure - Spectrogram of Flute C5 Note

A blue and yellow line graph

Description automatically generated

Figure - Spectrogram of Trumpet C5 Note

A blue and yellow lines

Description automatically generated

Figure - Spectrogram of Violin C5 Note

Plotted above are the same 4 instruments but this time I set the window length to be the full length of the signal. However, as we can see in the graphs above, we completely lose our ability to recognise any time domain effects such as the vibrato that was clearly evident in the violin and flute spectrograms in the previous section. But what we lose in the time domain we make up for in the frequency domain. Looking at the 4 graphs we can distinctly see all the frequencies that the instrument produced when playing the note. In reality, one would never set the window size to be the full length of the signal, since it defeats the whole point of using a spectrogram. The information in the spectrogram above would be better presented using a DFT of the original signal.

# Ex 1.3.2.1

A screen shot of a sound wave

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Figure - Spectrogram of Another Bites the Dust from 2'28 - 2'31

Analysing the spectrogram of a song can reveal a lot about what’s happening in the song. Looking at the spectrogram above we see a repeating impulse (circled in red) with frequency components across the spectrum from 0 - Hz. This is indicative of a rhythmic type of beat, most likely being the drums. I can be reasonably sure of this conclusion because drum kicks usually start around 50Hz, with their cymbals lying around 16kHz. The next feature to note in the spectrogram is the voice of Freddie Mercury (indicated by the purple box). Speech can be easily identified by the sinusoidal motion of the frequency components and its overtones that are quite close together. The motion also indicated some level of intentional vibrato in his voice. We can also hear from the sound clip, that his voice quickly reaches a peak before then lowering in pitch while he is vocalizing. This can also be seen in the spectrogram if we track the fundamental frequency in his voice (dashed red line). Also, towards the end of the audio clip (150.5 – 151 seconds) we can hear some reverb added to Freddie’s voice. However, I couldn’t pick this out on the spectrogram plot from MATLAB. I believe this is because the reverb just starts as our audio clip ends, so there isn’t enough information in the current spectrogram plot to make out the reverb.

# Ex 1.3.2.2

For the second audio clip I decided to focus on the seconds after the previous audio clip. Below I have shown a screenshot from the spectrogram view from Audacity since I feel it gives better resolution and clarity over the MATLAB one.

A screenshot of a computer screen

Description automatically generated

Figure - Spectrogram view of Another One Bites the Dust from 150 to 153 seconds.

Again, in this clip we can identify features such as the bass guitar (circled in black), as well as the drums (circled in green). We can also see Freddie’s vocalisation continue into this clip; however, we can also see the reverb effect that they applied to his voice past the 151 second mark. Since reverb is caused by the reflection of voice off objects in the room, this manifests as the smearing of frequencies in the time domain. This effect can clearly be seen when we compare the white and purple boxes. In the white box we can see that the shape of the frequencies is tight as Freddie is intentionally varying his pitch and voice to create the vocalisation. However in the purple box we see this same vocalisation except the frequencies have been smeared in the time domain, to simulate what reflections would sound like, hence creating the reverb effect.

# Ex 1.3.3.1

A blue and yellow striped pattern

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Figure - Spectrogram of Speech Audio (40ms window size)

A blue and yellow striped background

Description automatically generated

Figure - Spectrogram of Speech Audio (80ms window size)

A blue and yellow striped pattern

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Figure - Spectrogram of Speech Audio (150ms window size)

Shown above are 3 graphs of varying window sizes from 40ms to 150ms. The differences between the 3 spectrograms are apparent. From theory we know that a longer window size allow us to resolve individual frequency components better, however we do lose resolution in the time domain. In the first spectrogram we see that we can see some frequency components however, they look to be smeared across the frequency domain. But we do see we have excellent time domain resolution. Using the first graph, a trained audio expert could probably make out various sounds that the speaker was making. However, when we look at the last graph, we see that we can better resolve individual frequency components, but we begin to lose our time domain resolution. This explains the time-frequency trade off that come with spectrograms. We can increase our window length to resolve individual frequencies better, but we lose out ability to resolve events in the times domain such as impulses. Whereas a shorter window length allows us to resolve time domain events, but we lose resolution in the frequency domain. There is no optimal window length, and the choice comes down to the problem at hand.

# Ex 1.3.3.2

A blue and yellow line

Description automatically generated with medium confidence

Figure - Spectrogram of Speech Corrupted with Note 105 (40ms window size)

The above graph is a spectrogram of the same speech as in the previous exercise except now it has been corrupted with a tone of note 105, which corresponds to a signal of 3520Hz. This corruption is clearly seen as a bright signal at 3520Hz. Whereas the speech components lie between 0 and 2500Hz. This is an example of where spectrograms can be useful in audio processing. We can easily identify where the noise is and design a filter to cut out this noise. Spectrograms can also be useful to identify noise signals that change with time, these would be lost if we were to just plot a distribution of the frequency components and their power as in an FFT graph. A changing noise signal is shown in the spectrogram below:

A green and blue graph

Description automatically generated with medium confidence

Figure - Spectrogram of Speech with Varying Frequency Corruption (40ms window size)

# Ex 1.3.4

A graph of a graph

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Figure - Plot of normal and abnormal ECG

Shown above is an ECG plot of a normal and abnormal patient. We can easily identify some features of a normal ECG. Circled in blue is the P wave, this originates from the atria. We can then see the QRS complex. This reflects the depolarization of atria before the polarization of the ventricles. This is then normally followed by a variable size T wave which isn’t shown on this plot but is usually present in ECGs.

However, when looking at the abnormal ECG we don’t see any of these usual structures, and we see that the amplitude across the ECG is much higher than what is normally expected.

A screenshot of a graph

Description automatically generated

Figure - Spectrogram of Normal and Abnormal ECG Signals

Shown above is the spectrogram plot of the normal and abnormal signals. While this graphs don’t seem to provide too much information, we can still glean a lot of information from these plots. Looking at the normal ECG we can see the blip from the P wave around 0.1 seconds (indicated by the rise in frequency content). Then see another big rise in frequency content around 0.4 seconds. This is indicative of the QRS complex while the ventricles polarize. Whereas in the abnormal ECG graph can see the that distribution of frequencies is completely wrong. There is a lot of high frequency components in the beginning when instead it should be lower frequency components present.

However when compared to the time domain plot, the spectrogram is not as useful. Since in the time domain we have defined features that we can use to detect whether the heart is beating normally or is in arrhythmia.