

Lab10 Report

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Introduction

This lab course mainly focus on μ -law quantization and adaptive quantization, which automatically fits the smaller signal amplitude. In this lab, we also learns how to encode a speech using μ -law from bottom to the end and do several comparision between μ -law quantization and static quantization, which shows several advantages of encoding the speech siganal adaptively.

Problem 1

Problem description

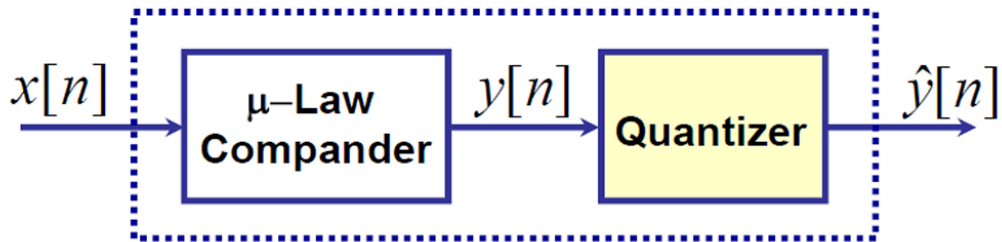
1. Plot the output waveform $y[n]$ of the μ - law compressor and plot a histogram of the output samples.
2. Write an m - file for the inverse of the μ - law compressor, named `mulawinv(y, mu)`. The function should follow a specific calling sequence and parameter definition. Test the inverse system by applying it to the output of `mulaw()` without quantization.
3. Compute and plot the first 8000 samples of the resulting quantization error, plot a histogram of the quantization error amplitudes, and plot the power spectrums of the resulting quantization errors.

Solutions and process

1. Use the given MATLAB function `mulaw()` to do the μ compression

2. Follow the steps shown in the figure, first calculate the amplitude, and then recover the sign by multiplying `sign(y)`

μ-Law Companding



$$y(n) = \ln |x(n)|$$

$$x(n) = \exp[y(n)] \cdot \text{sign}[x(n)]$$

- where $\text{sign}[x(n)] = +1 \quad x(n) \geq 0$
 $\quad \quad \quad = -1 \quad x(n) < 0$

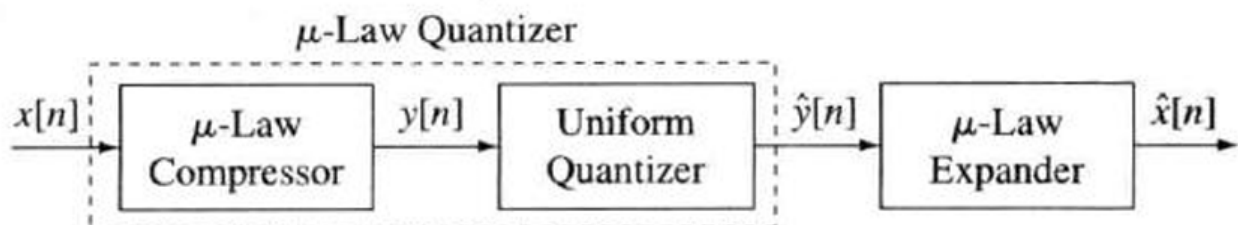
- the quantized log magnitude is

$$\hat{y}(n) = Q[\log |x(n)|]$$

$$= \log |x(n)| + \varepsilon(n) \quad \underline{\text{new error signal}}$$

53

3. First calculate \hat{y} using MATLAB function `fxquant()`, then calculate the error spectrum using `pspect()`



Key code segment

- 1.

```

x = (-1:0.001:1);
figure
plot(mulaw(x,1), 'Linewidth',1), hold on;
plot(mulaw(x,20), 'Linewidth',1), hold on;
plot(mulaw(x,50), 'Linewidth',1), hold on;
plot(mulaw(x,100), 'Linewidth',1), hold on;
plot(mulaw(x,225), 'Linewidth',1), hold on;
plot(mulaw(x,500), 'Linewidth',1), hold off;
title('Waveform After Encoding')
legend('1', '20', '50', '100', '225', '500');

```

2. Derive function `my_mulawinv()`

```

[y, fs] = audioread('s5.wav');
y = y(1300:18800);
figure
subplot(211)
plot(y), title('Original wavform')
subplot(212)
plot(mulaw(y, 225)), title('Encoded waveform')
saveas(gcf, "D:/作业提交/大三 下/语音信号处理/lab10/P1_b_1.png", 'png')
% 直方图
figure
histogram(mulaw(y, 225))
title('Histogram of Encoded waveform')
saveas(gcf, "D:/作业提交/大三 下/语音信号处理/lab10/P1_b_2.png", 'png')

function x = my_mulawinv(y, mu)
    % 计算幅度部分
    abs_x = ( (1 + mu) .^ abs(y) - 1 ) / mu;
    % 恢复符号
    x = abs_x .* sign(y);
end

```

3. Plotting the error power spectrum

```

yh_4 = fxquant(mulaw(x, 225), 4, 'round', 'sat');
yh_8 = fxquant(mulaw(x, 225), 8, 'round', 'sat');
yh_10 = fxquant(mulaw(x, 225), 10, 'round', 'sat');
yh_6 = fxquant(mulaw(x, 225), 6, 'round', 'sat');
e_4 = mulawinv(yh_4, 255) - x;
e_6 = mulawinv(yh_6, 255) - x;
e_8 = mulawinv(yh_8, 255) - x;
e_10 = mulawinv(yh_10, 255) - x;
e_4 = e_4(1:8000);
e_6 = e_6(1:8000);
e_8 = e_8(1:8000);
e_10 = e_10(1:8000);
% histogram
figure
subplot(221), histogram(e_4), title('Quantization Error with 4 bits')

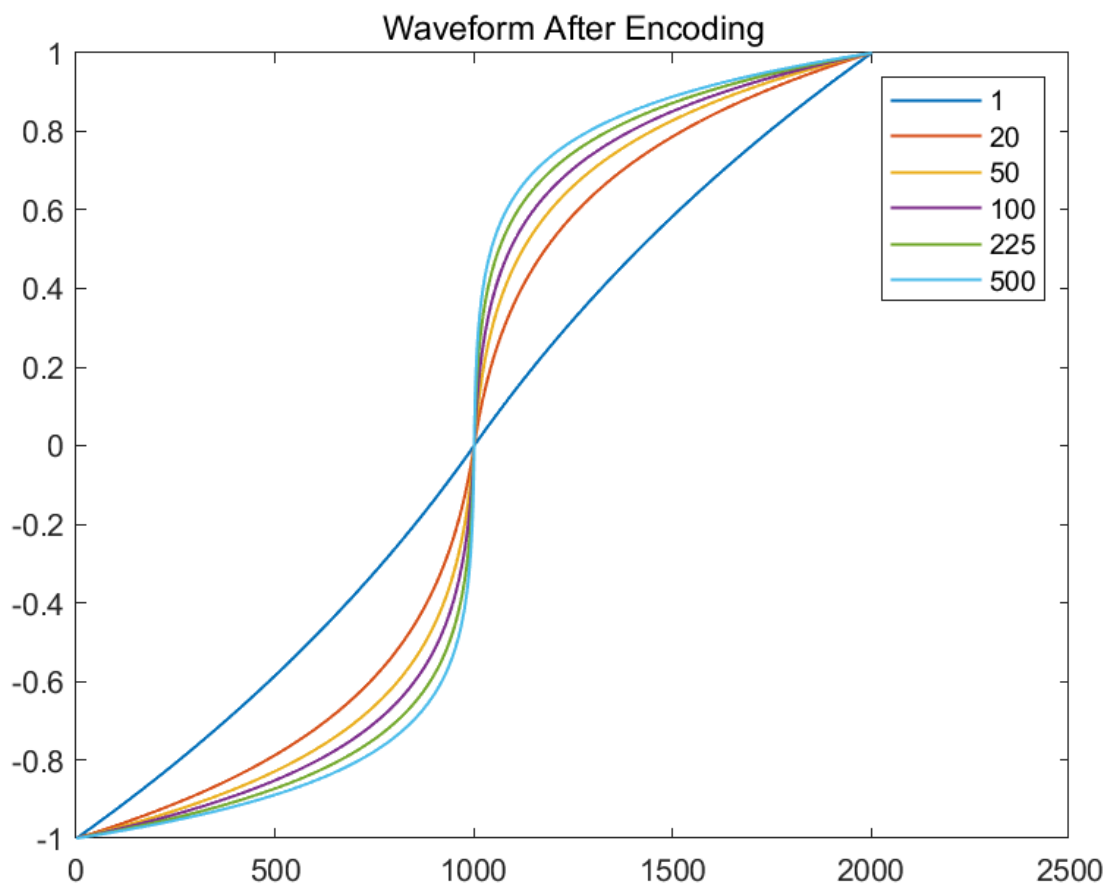
```

```
subplot(222), histogram(e_6), title('Quantization Error with 6 bits')
subplot(223), histogram(e_8), title('Quantization Error with 8 bits')
subplot(224), histogram(e_10), title('Quantization Error with 10 bits')
saveas(gcf, "D:/作业提交/大三 下/语音信号处理/lab10/P1_d_1.png", 'png')
```

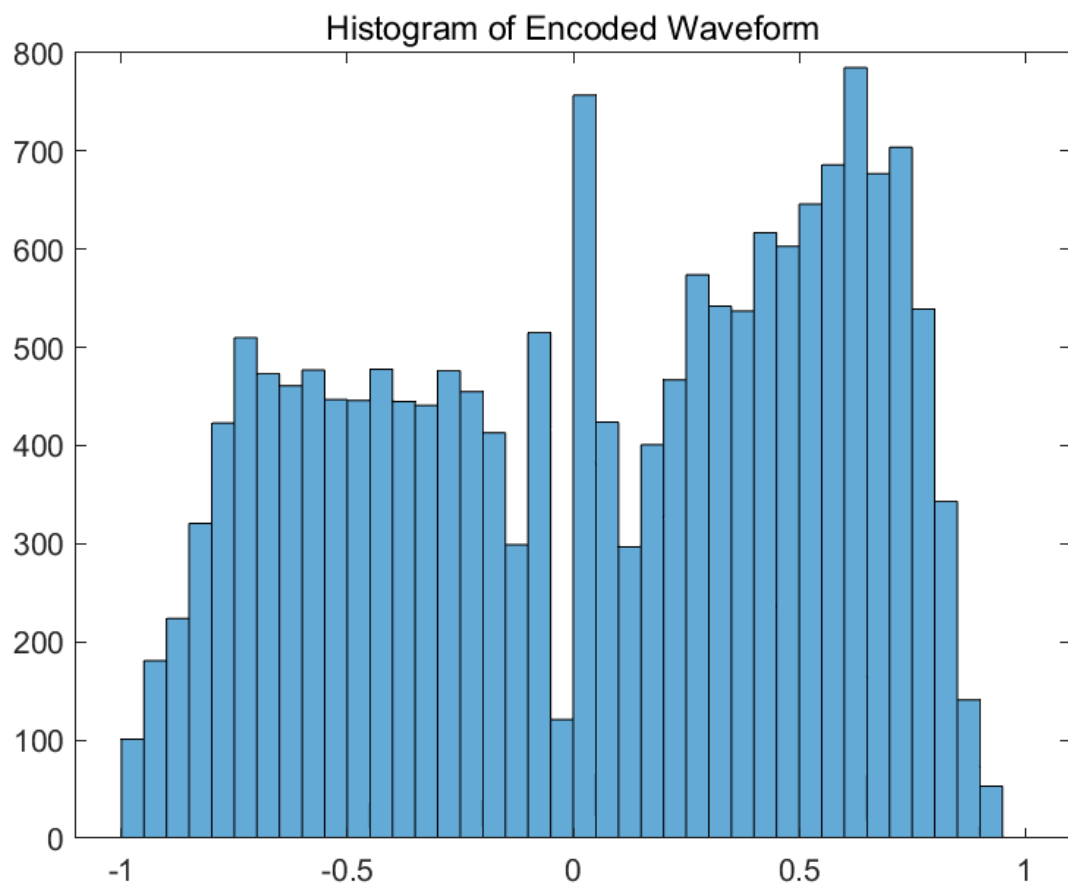
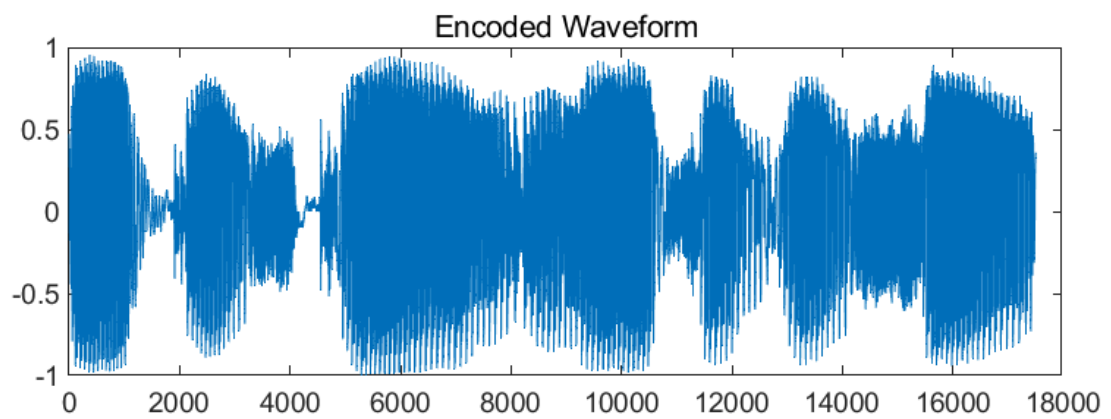
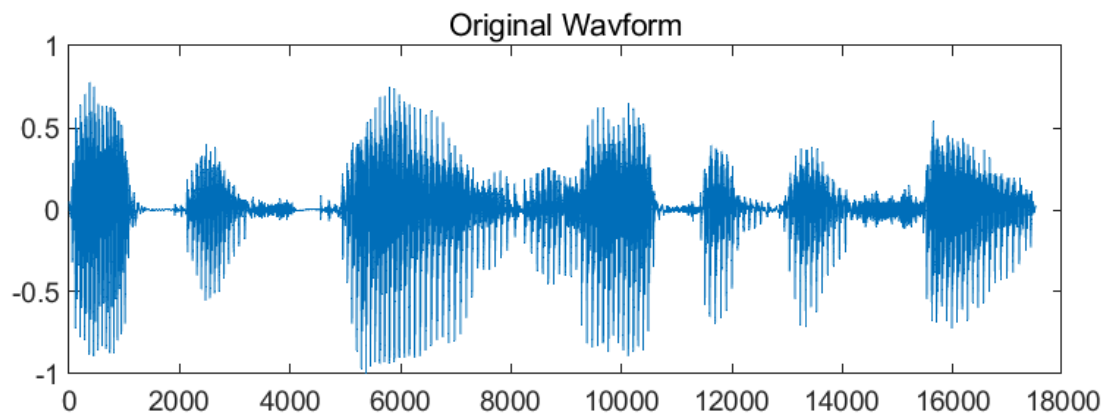
```
% Power Spectrum
win_len = 512;
[p_4, f4] = pspect(e_4, fs, win_len, win_len);
[p_6, f6] = pspect(e_6, fs, win_len, win_len);
[p_8, f8] = pspect(e_8, fs, win_len, win_len);
[p_10, f10] = pspect(e_10, fs, win_len, win_len);
figure
plot(f4, p_4, 'Linewidth',1), hold on;
plot(f6, p_6, 'Linewidth',1), hold on;
plot(f8, p_8, 'Linewidth',1), hold on;
plot(f10, p_10, 'Linewidth',1), hold off;
xlabel('Frequency (HZ)');
ylabel('Power Spectrum (dB)');
legend('4-bit', '6-bit', '8-bit', '10-bit');
saveas(gcf, "D:/作业提交/大三 下/语音信号处理/lab10/P1_d_2.png", 'png')
```

Result and Analysis

1. Question A



2. Question B



As we can see in the result, after encoding, the small amplitude are increased, which provide convenience

and accuracy for the following encoding and decoding.

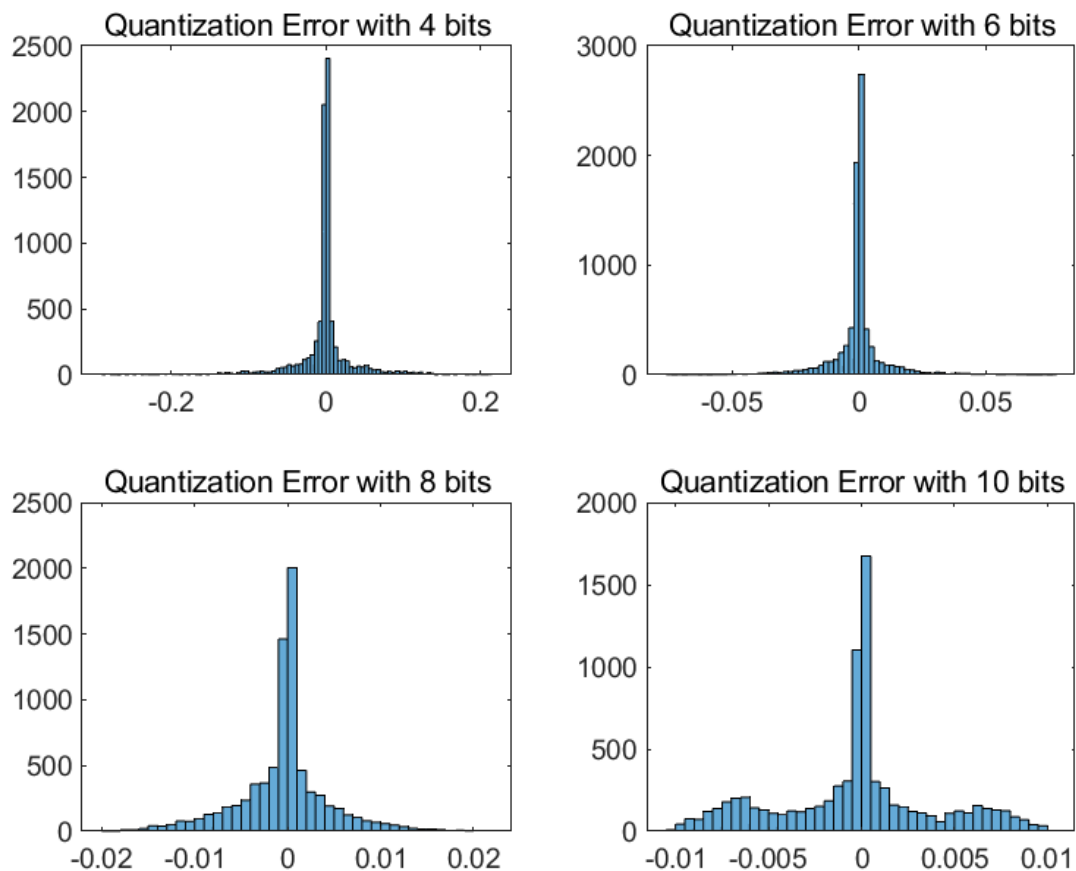
3. Question C

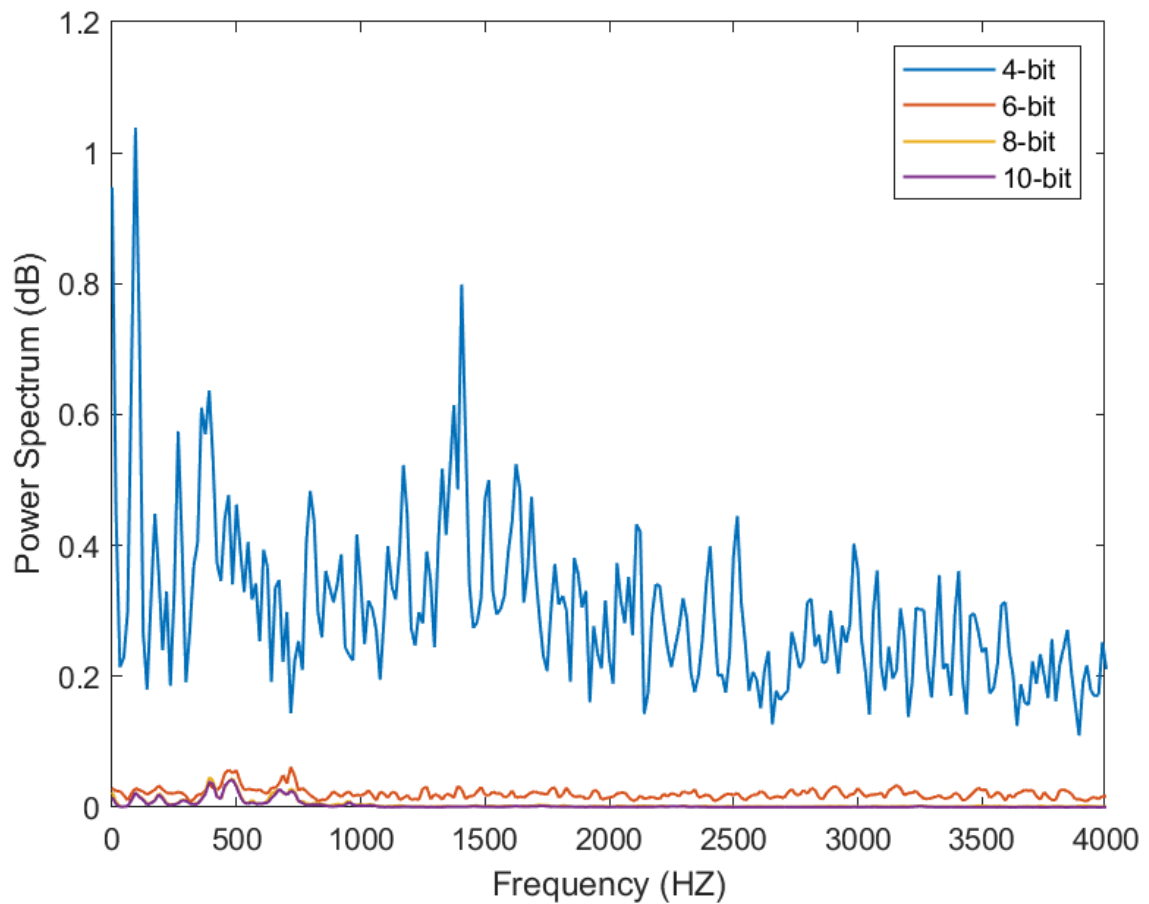
```
v = my_mu1awinv(mu1aw(y, 225), 225);  
mean(v-y)
```

In the code, we use the above method to derive the gap between v and original signal y . The result is $4.62 \cdot 10^{-19}$, which is small enough to prove the efficiency of `my_mu1awinv()`

4. Question D

We tested more situations aside from 6-bits(4, 8, 10 bits are all tested), and we can see that as the bit number increase, the error decrease evidently.





Problem 2

Problem description

1. Write function to compute SNR, output SNR in dB. Use it to compute SNRs for 8 - and 9 - bit uniform quantization of a s5.wav speech segment
2. Vary the input speech signal level and write a program to plot measured SNR for all 13 cases. Additionally, use different static quantization value and μ quantization value and compare its differences.

Solution and process

1. Derive a MATLAB function `SNR` to calculate the SNR for a uniform B-bit quantizer. The mathematical description is shown below:

$$\text{SNR} = 10 \log \left(\frac{\sum_{n=0}^{L-1} (x[n])^2}{\sum_{n=0}^{L-1} (\hat{x}[n] - x[n])^2} \right).$$

2. Compare the quantization result for different parameters and both static quantization and μ -bit quantization. To be concise, in the μ -bit quantization, first compress the original signal, then do a uniform quantization, thirdly, expand the μ -bit encoded signal and finally calculate the SNR.

Key code segment

1. Derive the SNR function based on the formula above

```
[y, fs] = audioread('s5.wav');
% mu-量化
y_new = mulaw(y, 225);
% 均匀量化
yh_8 = fxquant(mulaw(y, 225), 8, 'round', 'sat');
yh_9 = fxquant(mulaw(y, 225), 9, 'round', 'sat');
yh_10 = fxquant(mulaw(y, 225), 10, 'round', 'sat');
yh_11 = fxquant(mulaw(y, 225), 11, 'round', 'sat');
yh_12 = fxquant(mulaw(y, 225), 12, 'round', 'sat');
% s = y - yh_8
[snr_8, e_8] = SNR(yh_8, y_new);
[snr_9, e_9] = SNR(yh_9, y_new);
[snr_10, e_10] = SNR(yh_10, y_new);
[snr_11, e_11] = SNR(yh_11, y_new);
[snr_12, e_12] = SNR(yh_12, y_new);
bit = [8,9,10,11,12];
snr = [snr_8, snr_9, snr_10, snr_11, snr_12];
figure
stem(bit, snr), xlabel('Bits Number'), ylabel('SNR (dB)'), title('SNR for Uniform
Quantization')
grid on

function y = mulaw(x, mu)
    y = sign(x) .* log(1 + mu * abs(x)) / log(1 + mu);
end
```



```

function [snr, e] = SNR(xh, x)
    L = length(x);
    sum_sig = 0;
    sum_err = 0;
    for i=1:L
        sum_sig = sum_sig + x(i).^2;    % 分号!!!
        sum_err = sum_err + (x(i)-xh(i)).^2;    % 分号!!!
    end
    sum_sig
    sum_err
    snr = 10*log10(sum_sig/sum_err)
    e = mulaw(xh, 225) - x;
    %     mean(e)
end

```

2. Compare all situations in one figure.

```

% 参数设置
factors = 2.^(0:-1:-12);
mu_values = [100, 255, 500];
bits_uniform = 6:10;

% 初始化存储矩阵
snr_uniform = zeros(length(factors), length(bits_uniform));
snr_mulaw = zeros(length(factors), length(mu_values));
inv_sigma_x = zeros(length(factors), 1);

% 计算不同幅度下的SNR
for i = 1:length(factors)
    x_scaled = x * factors(i);
    sigma_x = std(x_scaled);
    inv_sigma_x(i) = 1 / sigma_x;

    % 均匀量化
    for j = 1:length(bits_uniform)
        x_quant = fxquant(x_scaled, bits_uniform(j), 'round', 'sat');
        snr_uniform(i,j) = 10 * log10( sum(x_scaled.^2) / sum((x_scaled - x_quant).^2) );
    end

    % μ-law量化 (6 bits)
    for k = 1:length(mu_values)
        % μ-law压缩
        y = mulaw(x_scaled, mu_values(k));
        % 均匀量化 (6 bits)
        y_quant = fxquant(y, 6, 'round', 'sat');
        % μ-law扩展
        x_recon = mulawinv(y_quant, mu_values(k));
        % 计算 SNR (dB)
        snr_mulaw(i,k) = 10 * log10( sum(x_scaled.^2) / sum((x_scaled - x_recon).^2) );
    end
end
end

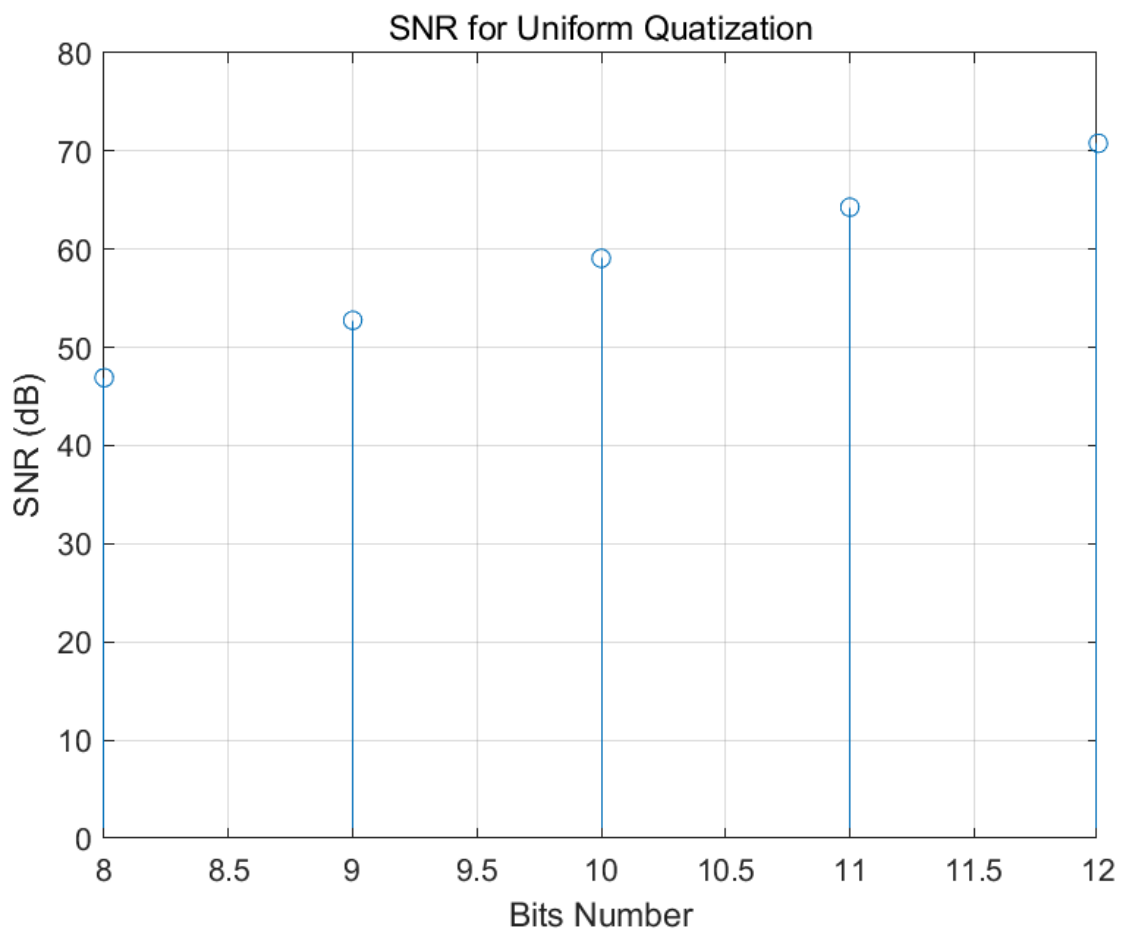
```

```
figure;
semilogx(inv_sigma_x, snr_uniform, 'Linewidth', 1.5); hold on;
semilogx(inv_sigma_x, snr_mulaw, '--', 'Linewidth', 2);
xlabel('1/\sigma_x'); ylabel('SNR (dB)');
title('SNR vs 1/\sigma_x for Uniform and \mu-law Quantization');
grid on;

legend_labels = [...
    arrayfun(@(b) sprintf('%dbit', b), bits_uniform, 'UniformOutput', false), ...
    arrayfun(@(mu) sprintf('\mu-law (\mu=%d)', mu), mu_values, 'UniformOutput', false) ...
];
legend(legend_labels, 'Location', 'southwest');
```

Result and Analysis

1. As shown in the result, whenever one bit is added, the SNR increases approximately 6dB, which fits the tone.



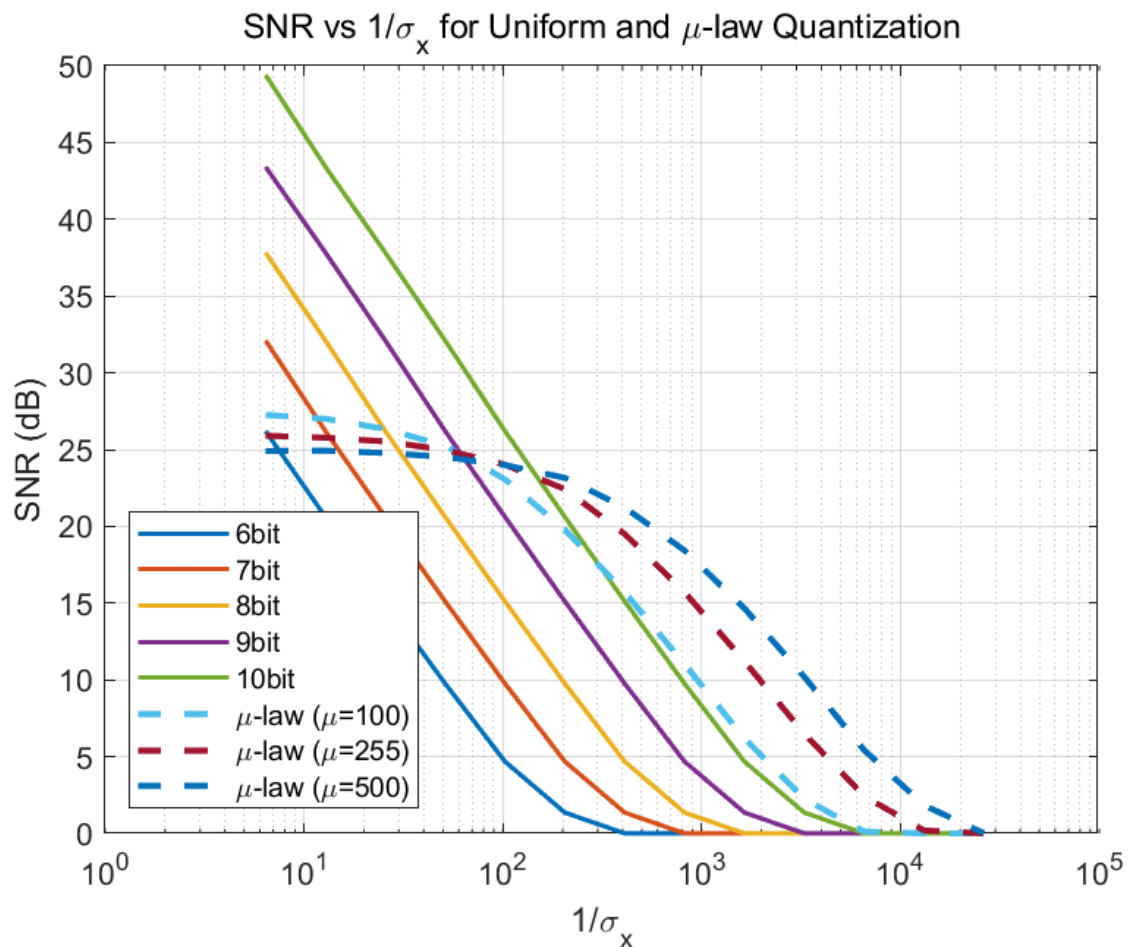
2. For μ -law quantization:

- When $1/\sigma_x$ varies the SNR remains relatively stable.
- Optimal performance is achieved at $\mu=255$ (standard parameter for telephone speech coding).

3. For Uniform quantization:

- The SNR degrades sharply as the signal amplitude decreases (due to higher quantization errors for small signals).

- Approximately ~12 bits are required to match the dynamic range of 6-bit μ -law quantization.



Problem 3

- Problem description:**

This exercise focuses on demonstrating the process of adaptive quantization using both IIR and FIR filters. The task involves processing a given speech file, `s5.wav`, and calculating the standard deviation $\sigma[n]$ of the signal.

- Solution and Process:**

As the expressions of filters are already given, the coefficients for FIR and IIR are determined. We will use those coefficients and the `filter` function to calculate the deviation, and at last use those calculated deviation values to equalize signals.

Effects of different parameters (alpha and M) will be discussed.

- Key code segment:**

- The IIR filters are designed using `b` and `a` coefficients, and applied using `filter()`. Be careful that the input here is squared audio signal.

```
alpha_1 = 0.9;
alpha_2 = 0.99;

b_1 = [0 (1-alpha_1)];
b_2 = [0 (1-alpha_2)];
```

```

a_1 = [1 -alpha_1];
a_2 = [1 -alpha_2];

[aud, fs] = audioread('s5.wav');
aud = aud - mean(aud);
aud_squared = aud.^2;

delta_1 = sqrt(filter(b_1, a_1, aud_squared));
delta_2 = sqrt(filter(b_2, a_2, aud_squared));

gain_equalized_1 = aud ./ delta_1;
gain_equalized_2 = aud ./ delta_2;

```

Superimposed Plots are drawn using `hold on;` command.

```

figure(3)
plot(aud(2700:6700));
title('S5 Original signal');
xlabel('Sample Number'); ylabel('Amplitude');

```

original waveform is drawn for comparison.

2. FIR filter is designed using a similar manner.

```

M_1 = 10;
M_2 = 100;

b_fir_1 = ones(1, M_1) / M_1;
b_fir_2 = ones(1, M_2) / M_2;

delta_fir_1 = sqrt(filter(b_fir_1, 1, aud_squared));
delta_fir_2 = sqrt(filter(b_fir_2, 1, aud_squared));

gain_equalized_fir_1 = aud ./ delta_fir_1;
gain_equalized_fir_2 = aud ./ delta_fir_2;

```

```

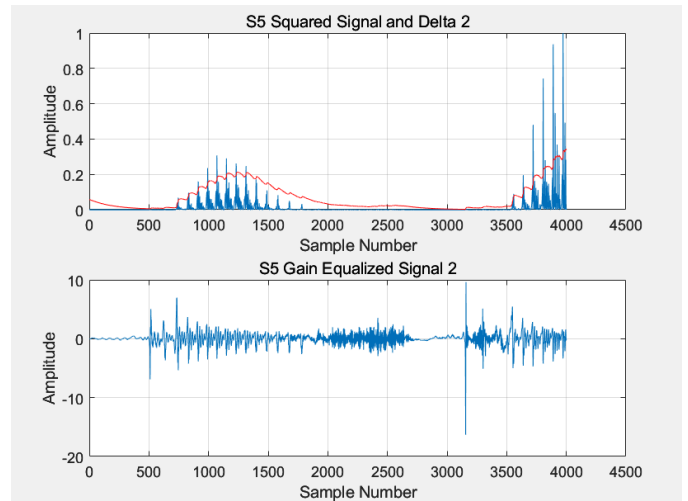
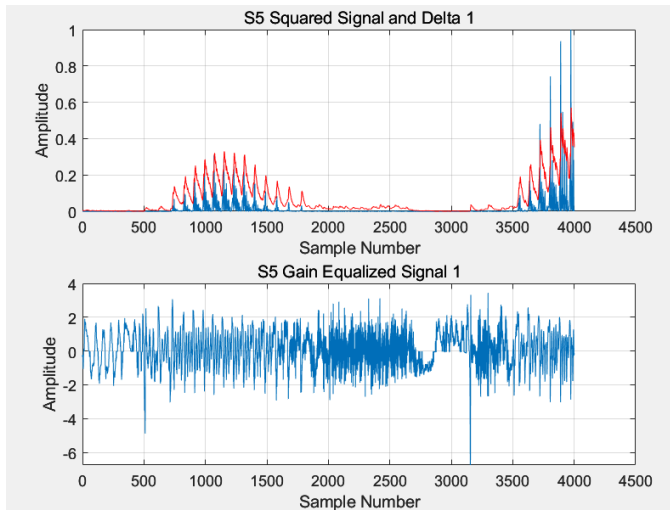
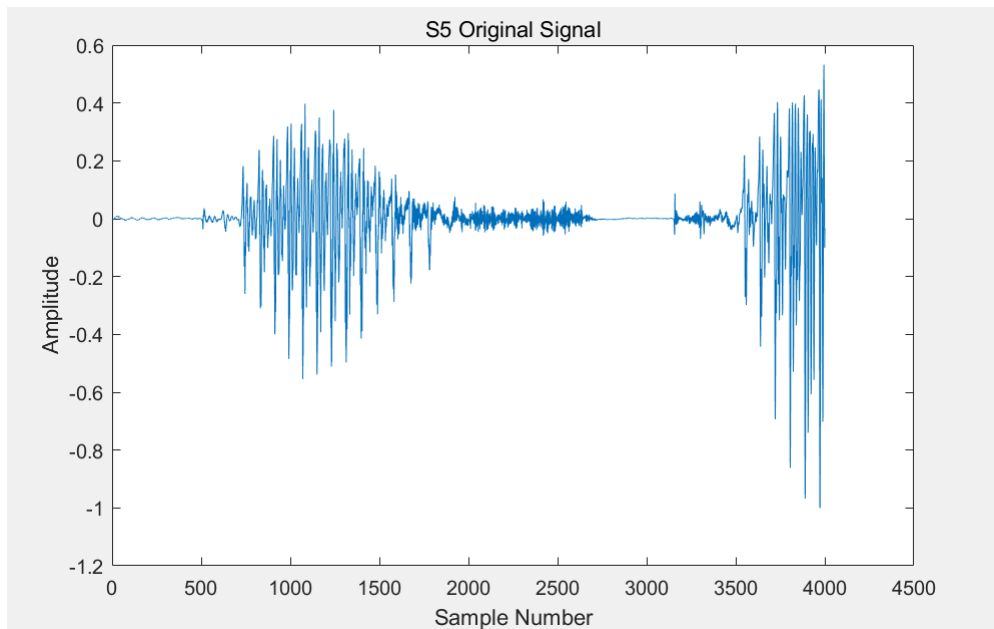
figure(4)
subplot(2,1,1);
plot(aud_squared(2700:6700)); hold on;
plot(delta_fir_1(2700:6700), 'r'); hold off;
title('S5 Squared Signal and FIR Delta 1');
xlabel('Sample Number'); ylabel('Amplitude');
grid on;

subplot(2,1,2);
plot(gain_equalized_fir_1(2700:6700));
title('S5 Gain Equalized FIR Signal 1');
xlabel('Sample Number'); ylabel('Amplitude');
grid on;

...

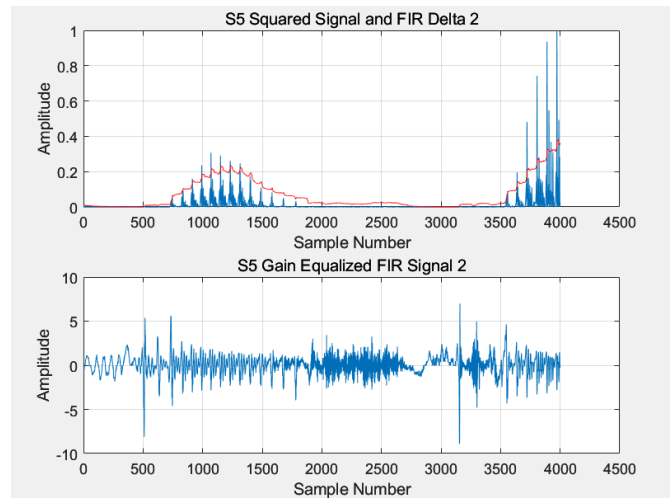
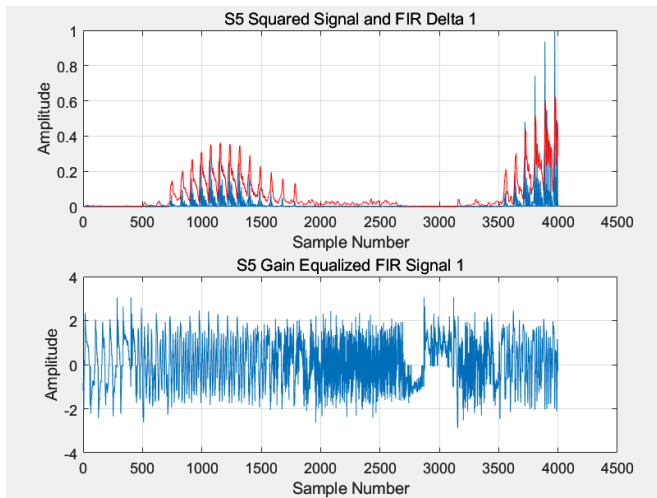
```

- **Results and Analysis:**



Delta 1 corresponds to $\alpha=0.9$, and delta 2 corresponds to $\alpha=0.99$.

Here $\alpha=0.9$ have a larger rate of adapting to the changing speech level. The overall level of the signal is equalize to approximately the same, although in $x=2800$ there are some abnormalities. On the contrary, the equalizer using $\alpha=0.99$ mostly does compression for large signal levels, and is less sensitive to rapid changes.



The results using FIR is mostly the same, with smaller M corresponding to smaller α .

Also for Delta 2, the deviation is more stable for both the overall waveform and the near-zero initial values. Also, the equalized FIR signal has a bigger amplitude than the IIR equalized signal.

Conclusion

In this lab, we explored μ -law quantization and adaptive quantization techniques for speech signals.

- **μ -Law Quantization:** The process significantly increases the amplitude of small signals, improving encoding accuracy. Our experiments showed that the quantization error decreases as the number of bits increases, with 10-bit quantization closely resembling white noise. The inverse μ -law function was validated, showing minimal reconstruction error.
- **SNR Analysis:** Comparing uniform and μ -law quantization methods, it was observed that for every additional bit in uniform quantization, the SNR improved by approximately 6 dB. In contrast, μ -law quantization maintained relatively stable SNR values across varying signal levels, achieving optimal performance at $\mu=255$, a standard parameter for telephone speech coding.
- **Adaptive Quantization:** Using both IIR and FIR filters to dynamically adjust quantization based on signal characteristics demonstrated that smaller α values (IIR) or M values (FIR) allowed faster adaptation to changes in speech levels. However, larger α or M values provided more stable deviation handling but were less responsive to rapid changes.

In summary, μ -law quantization offers significant advantages over static uniform quantization in terms of dynamic range and fidelity, especially for low-amplitude signals. Adaptive quantization techniques further enhance these benefits by adjusting to signal dynamics, ensuring better performance in real-world applications.