EEE431 Telecommunications I

Project 1 Report

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We record a piece of speech with a certain sampling frequency, greater than the Nyquiest rate and form a vector with resulting samples. This data has 1 million samples. The original speech signal can seen below:

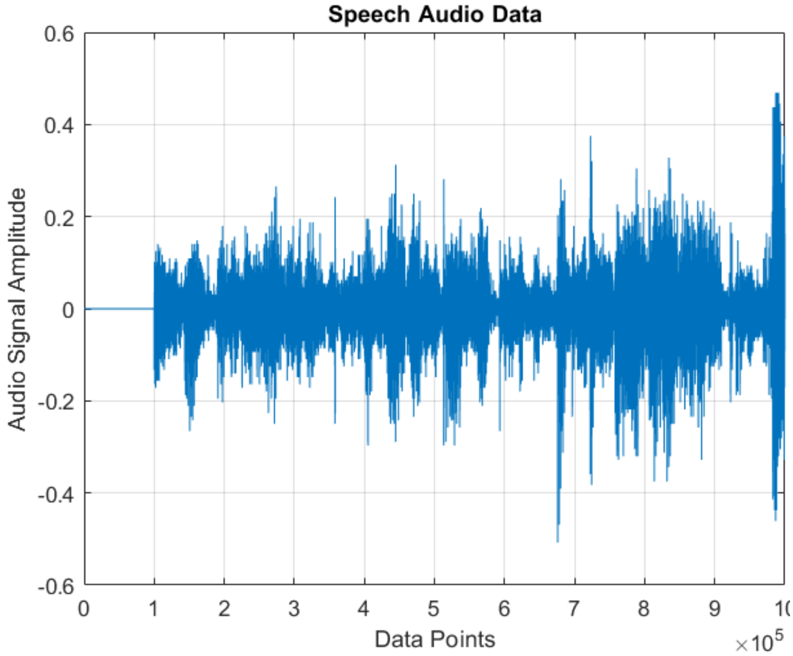

Figure 1: Speech Audio Signal

After removing the silent periods from the speech signal and normalizing this signal so shat all the signal amplitudes are in the interval [-1,1], it becomes as it follows:

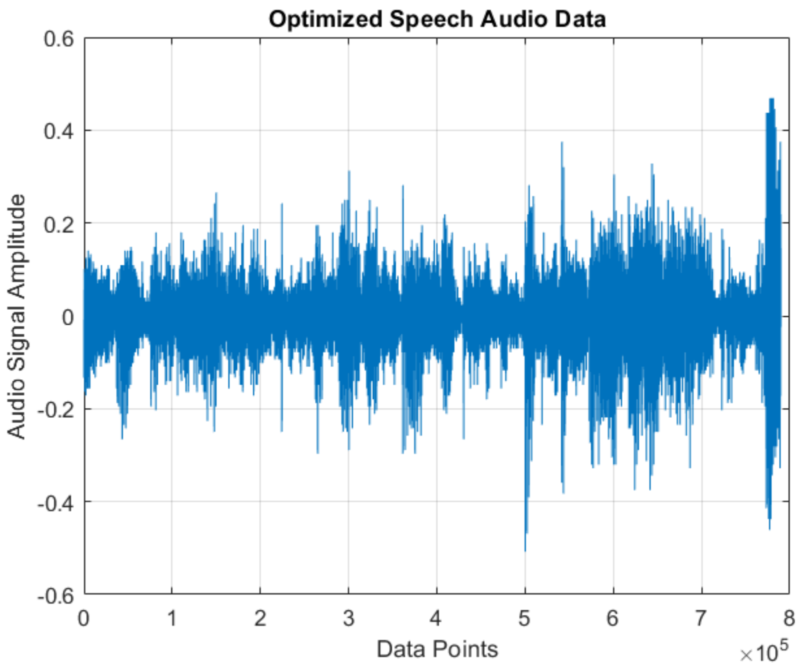

Figure 2: Silence Removed and Optimized Speech Audio Signal

Part 1)

1)

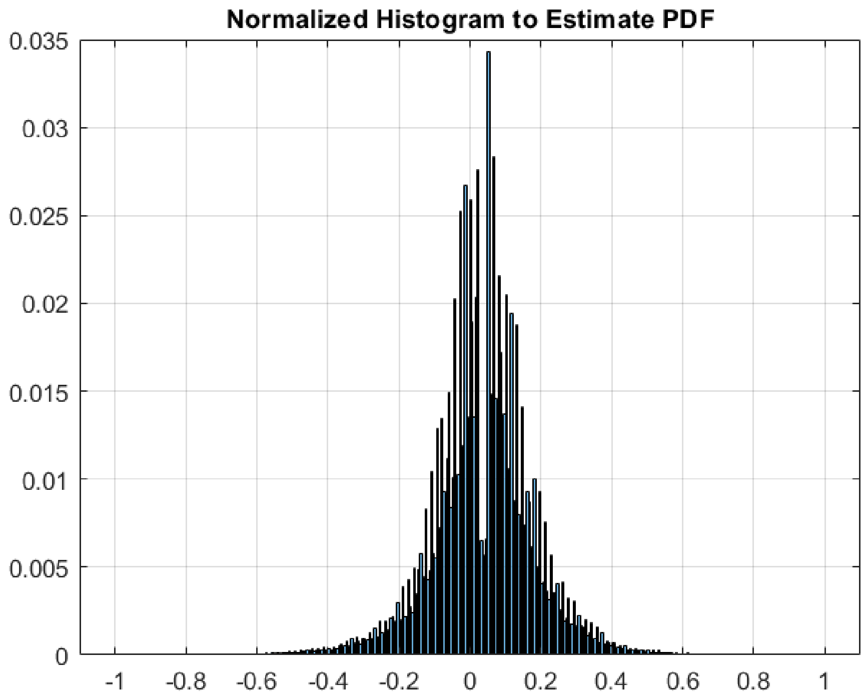

Figure 3: Normalized Histogram of the Speech Audio Signal

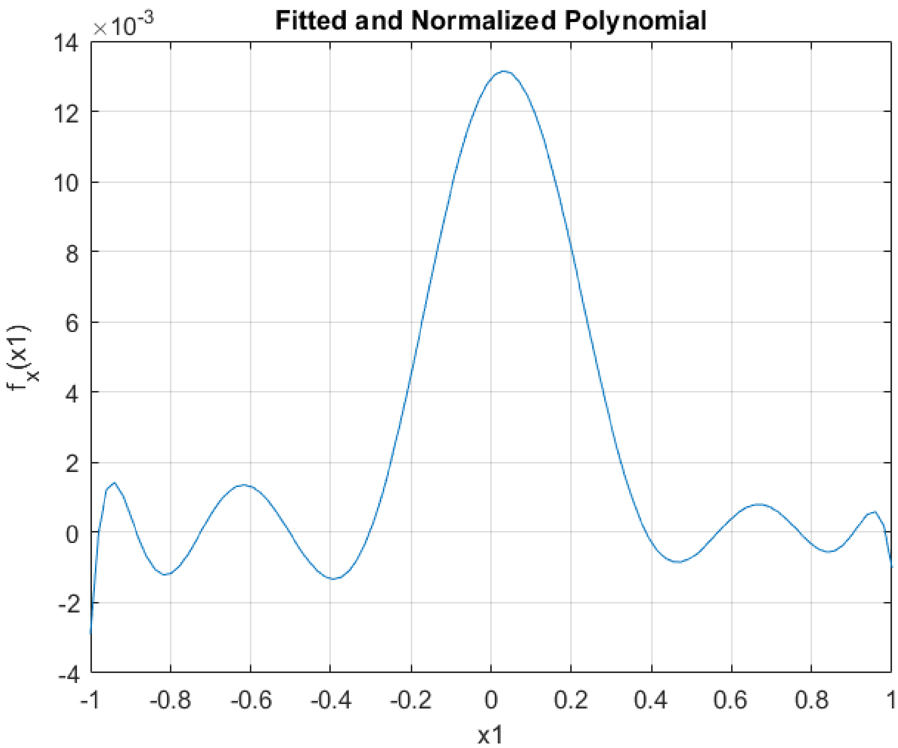

Figure 4: PDF Estimate of the Speech Audio Signal using Normalized Polynomial Fit

The histogram serves as a statistical graphic that shows the distribution of the samples according to the amplitudes of the signals and the number of samples with that specified amplitude. Therefore, histogram let us to approximate a probability density function of the signal. I used 10^{th} degree polynomial to fit this polynomial to the histogram, meaning that a 10^{th} degree polynomial, calculated by MATLAB, can well approximate the PDF and serve as PDF.

The signal is normalized and the amplitudes are in interval [-1,1]. From the histogram and PDF estimate of the speech audio signal, it can be observed that PDF estimate looks like a Normal PDF in the range [-1,1] and therefore the source samples are Gaussian Random Variables in the interval [-1,1].

Analyzing the Figure 4 further, it can be observed it is not a perfect bell shaped curve because it is just an approximated function and therefore not same as the theoretically perfect one.

2)

Uniform quantizer is implemented on MATLAB.

For the Uniform Quantizer:

N	MSE Distortion	SQNR
16	0.00130482101114703	14.9197615489528
64	8.33964419637443e-05	224.954674818230
256	2.23303632916071e-05	961.972068182785

Table 1: MSE Distortion and SQNR for Uniform Quantizer for Quantization Levels N = 16, 64, 128

As it can be seen, SQNR increases and MSE Distortion decreases as we increase the number of quantization levels, because higher number of quantization levels mean higher accuracy and higher definition.

3)

Non-Uniform Quantizer is implemented on MATLAB using Lloyd-Max iterative algorithm.

For the Non-Uniform Quantizer:

N	MSE Distortion	SQNR
16	0.00133712858152808	26.9253449933332
64	8.868292962290354e-05	213.734071821675
256	2.07382732373657e-05	1157.64362460072

Table 2: MSE Distortion and SQNR for Non-Uniform Quantizer for Quantization Levels N = 16, 64, 128

Comparing the uniform and nonuniform quantizers, it can be seen that although uniform quantizer is easier to implement, nonuniform quantizer is more successful, looking at the SQNR and MSE Distortion values. The reason is that the properties of the nonuniform quantizer is not deterministic unlike the uniform on, i.e level boundaries and the quantization values are not known beforehand. To implement the non-uniform quantizer, we use Lloyd-Max iterative algorithm that optimizes the level boundaries and quantization values iteratively throughout the process and therefore the results are more efficient and successful than the uniform quantizer. In addition, it is expected that distortion decreases as N increases, because increasing N - quantization levels increases the precision and accuracy of the quantization, as number of intervals increase and signal to be quantized can find the appropriate quantization level more successful, compared to lower N value.

4) A new speech audio is recorded.

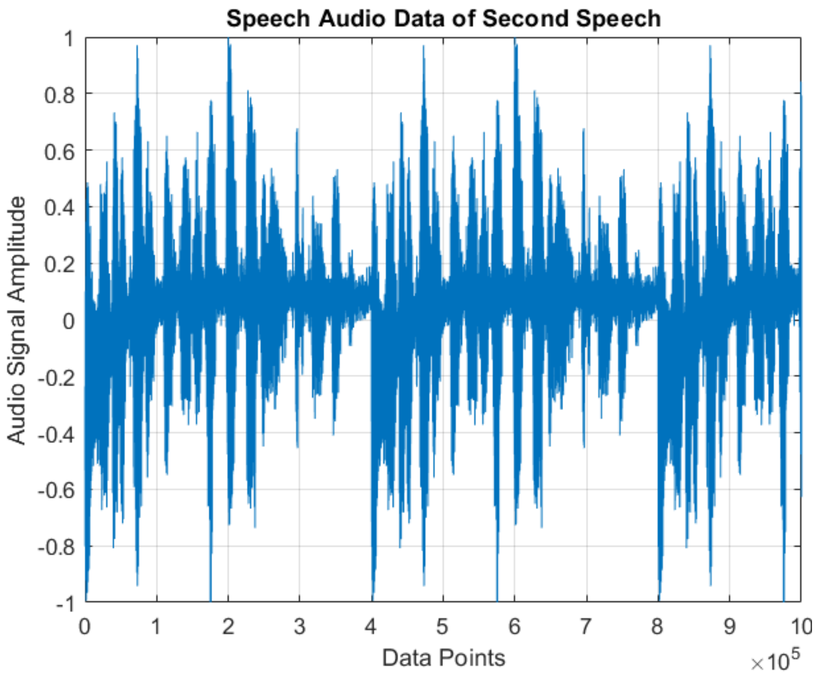

Figure 5: Speech Audio Signal

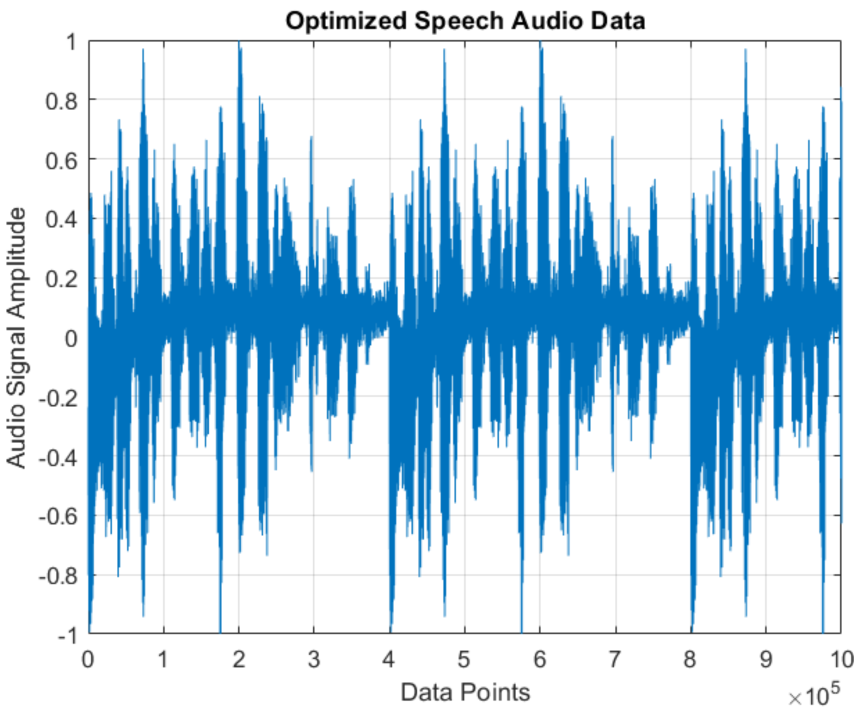

Figure 6: Silence Removed and Optimized Speech Audio Signal

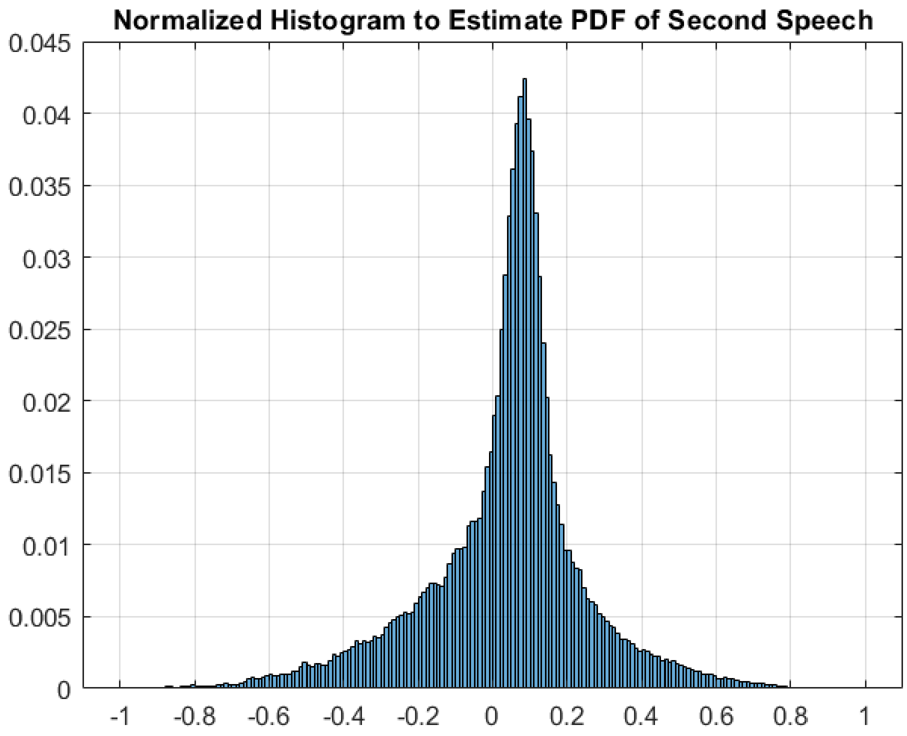

Figure 7: Normalized Histogram of the Second Speech Audio Signal

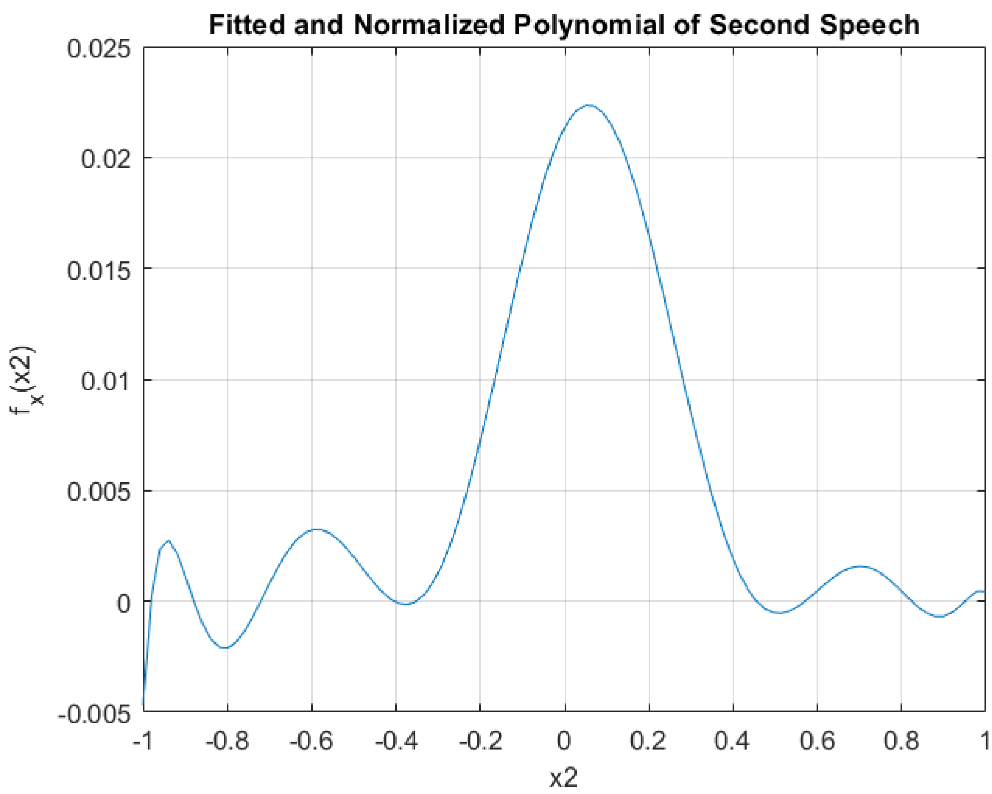

Figure 8: PDF Estimate of the Second Speech Audio Signal using Normalized Polynomial Fit

For the Uniform Quantizer on new speech audio signal:

N	MSE Distortion	SQNR
16	0.001612910550459	12.36833331200311
64	0.000440809919724	269.2865573119133
256	0.000149583213876	489.0444444444444

Table 3: MSE Distortion and SQNR for Uniform Quantizer for Quantization Levels N = 16, 64, 128

For the Non-Uniform Quantizer on new speech audio signal:

N	MSE Distortion	SQNR
16	0.00136557322979282	15.03019938287652
64	0.00109845612207881	216.4977946332580
256	0.00014044410174235	580.9741092490087

Table 4: MSE Distortion and SQNR for Non-Uniform Quantizer for Quantization Levels N = 16, 64, 128

Another speech signal is recorded and same procedures and algorithms, as for the first one, are applied. The results can be seen on the Tables 3 and 4, above.

About the uniform quantizer algorithm, it can be said that the performance totally depends on the signal itself, not on the quantizer, because the parameters such as quantization levels and level boundaries are deterministic and pre-calculated i.e they are calculated before the quantization, it is not an evolving algorithm.

About the nonuniform quantization, this process is different from the uniform one, as Lloyd-Max algorithm is an iterative algorithm i.e it is evolving according to the signal that it is used for. Therefore, this quantizer gets optimized for a specific signal. As a conclusion, as we have designed the nonuniform quantizer for the first signal, it is expected to perform worse on the second signal.

Part 2)

In this part, we are to prefer the error metric to be mean absolute value, instead of the squared error. For the nonuniform quantizer, Lloyd-Max quantizer algorithm has some modifications to minimize the expected value of the absolute value.

For the Uniform Quantizer:

N	Absolute Value Distortion	SQNR
16	0.268811505920365	0.088468433342253
64	0.009718497452376	2.447017443764691
256	0.004780997431811	4.974136282716986

Table 5: MSE Distortion and SQNR for Uniform Quantizer for Quantization Levels N = 16, 64, 128 with the Mean Absolute Value Error Metric

Non-Uniform Quantizer is implemented on MATLAB using Lloyd-Max iterative algorithm.

For the Non-Uniform Quantizer:

N	Absolute Value Distortion	SQNR
16	0.175818042813456	0.556954364994662
64	0.007946100917431	2.510541396064844
256	0.002921444954128	6.828475498855073

Table 6: MSE Distortion and SQNR for Uniform Quantizer for Quantization Levels N = 16, 64, 128 with the Mean Absolute Value Error Metric

Analyzing the results of the algorithms with new error metrics, mean absolute value, it can be stated that performance of the quantizer decreased drastically. One of the reasons is mean square error (MSE) amplifies the errors and therefore force quantizer to optimize the system better, which increases the overall performance. In addition, comparing the uniform and nonuniform quantizers with this new system, the performance of the nonuniform one is close to uniform one, meaning that the ability of nonuniform quantizer to optimize itself to increase the performance and therefore be better than uniform quantizer is deteriorated.

Part 3)

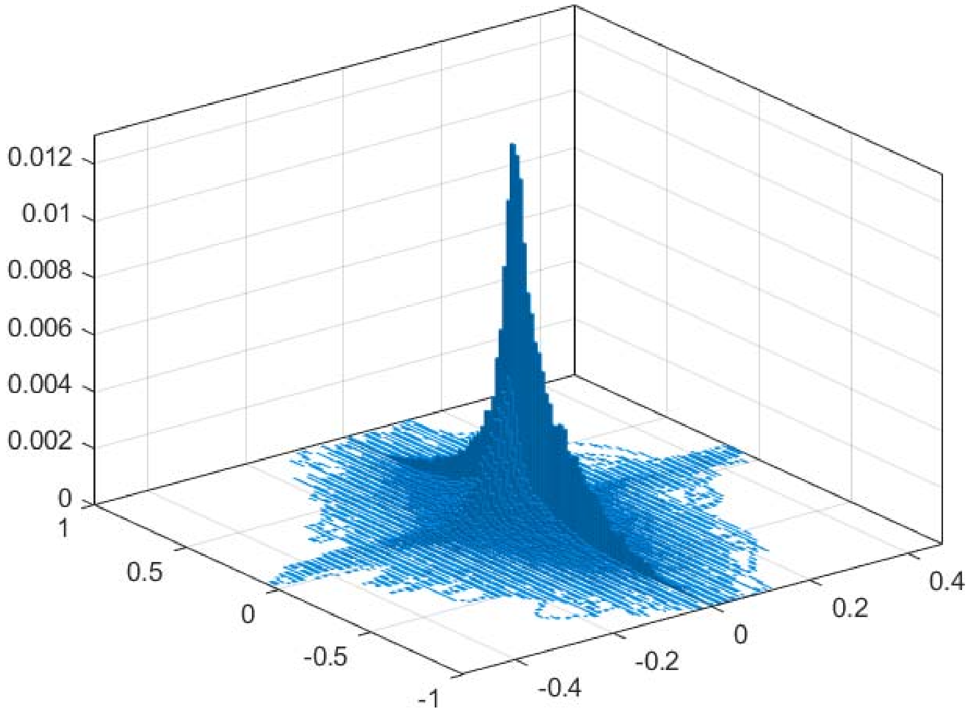

Figure 9: Joint PDF of Two Consecutive Samples of the Speech Source

Observing the Figure 9, above, we see joint PDF of the two consecutive samples of the speech source, two audio signal inputs in our case. The samples are not correlated and this can be seen on this figure. The difference between the scalar quantization and vector quantization is that for the scalar one, input is processed and quantized one sample at time, whereas for the vector quantization, the quantization is done with multiple source samples jointly, which increases the performance (SQNR) for the same rate encoding. Therefore, vector quantization is a good structure for quantizing two samples at a time, with a significant performance improvements over scalar quantizer structure.