QUANTIFYING THE EFFECTS OF LOSSY DIGITAL AUDIO COMPRESSION ALGORITHMS ON ELECTRIC NETWORK FREQUENCY SIGNALS IN FORENSIC ANALYSIS

by

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Quantifying the Effects of Lossy Digital Audio Compression Algorithms on Electric Network Frequency Signals in Forensics Analysis

Thesis directed by Associate Professor Catalin Grigoras

ABSTRACT

In forensic analysis, the electric network frequency can often be used to determine the time and date that an audio recording was created. Many forensic scientists working with media question the quality and validity of audio evidence that was created by or has been converted to lossy compressed audio formats. The following work outlines a study designed to quantify the effects of lossy compression algorithms on electric network frequency signals. It shows that no forensic analysis based on the electric network frequency should be disregarded in legal proceedings solely for the reason that the audio file had been converted to any of the ten algorithms tested in this study.

This abstract accurately represents the content of the candidate's thesis. I recommend its publication.

Signed ____________________________________

Catalin Grigoras

DEDICATION

I dedicate this thesis to my parents, Paul Archer and Lecia Barker, as well as Zak Archer, Joe and Lainey Archer, Amy Archer, and Bill Aspray. Without the guidance and support of my family, this would not have been possible.

ACKNOWLEDGMENT

I would like to give special thanks to Catalin Grigoras for his guidance and support during the process of my graduate education and throughout the creation of this thesis. I would also like to thank Jeffrey M. Smith for his instruction and Lorne F. Bregitzer for his participation on my committee.

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1. Introduction

Alternating current electricity is used to power the vast majority of the world. In most countries, the frequency of the electric current is either 50 or 60 Hz. In the United States, 60 Hz is used. In an ideal situation, the frequency would remain constant at precisely 60 Hz. However, based on the consumption of electricity across a power grid, the frequency constantly varies randomly within 0.6 Hz [1]. There are three power grids in the United States (Eastern, Western, and Texas), each of which has a different variation. Across any power grid, the electric network frequency (ENF) is almost the same including the variations [1][2][3]. The following figure shows the nearly identical variations in ENF across a power grid in Europe.

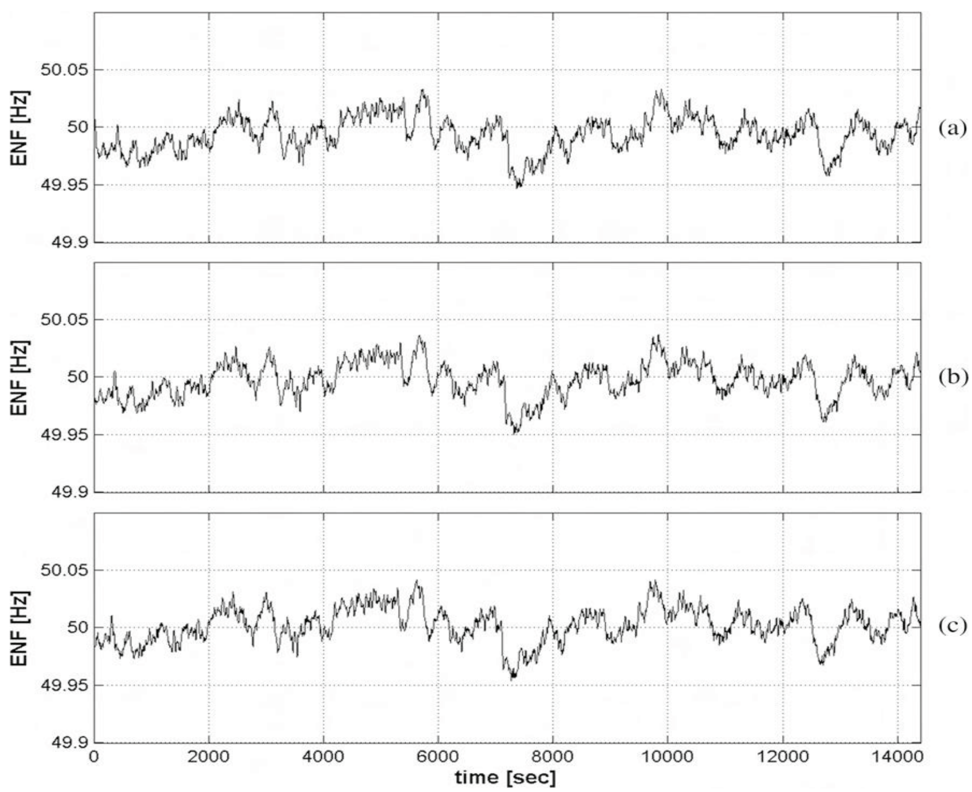

Figure 1.1 ENF Interlaboratory Results. (a) Bucharest, (b) Amsterdam, (c) Madrid. Courtesy, Grigoras [1].

Widespread use of portable audio recorders in consumer and law enforcement settings has caused a dramatic increase in the amount of digital audio evidence used in legal proceedings. The ENF is often captured by devices used to record audio signals, whether the signal is transmitted through sound pressure waves, by electromagnetic fields, or directly induced by the power supply of a recording device. Electromagnetic fields are present, however faint they may be, in most locations where power is distributed throughout a building. A recording device may pick up ENF through these fields whether it is a battery operated device or if it is powered from the power grid. This does not mean with certainty that the ENF signal will be present in every audio file produced under the above circumstances nor that the signal will necessarily be pronounced enough to perform an analysis.

For forensic purposes, because the variations in the ENF are random, they can be used to determine the exact time that an audio file was made by matching the variations of a forensic recording with a period of time in an ENF database. For that reason, databases of the exact ENF are now being recorded in various locations around the world. Verifying a claimed time and date of recording with the use of ENF analysis is one of many criterions used in the authentication of a digital audio recording, though the ENF analysis alone is not adequate evidence of authenticity. According to the Audio Engineering Society Standard AES27-1996 (r2007), an authentic audio recording is defined as "a recording made simultaneously with the acoustic events it purports to have recorded, and in a manner fully and completely consistent with the method of recording claimed by the party who produced the recording; a recording free from unexplained artifacts, alterations, additions, deletions, or edits" [6].

Methods of using ENF analysis to authenticate a forensic audio recording have been presented by Sanders [2], Grigoras [1], and Cooper [4]. Methods of analyzing ENF include a frequency against time analysis involving visual examinations of spectrograms, frequency domain analysis in which the frequency with the maximum magnitude for each unit of time is used to produce a series of ENF values, and a time domain analysis in which zero crossings of a band passed signal are used to determine the ENF.

Unfortunately, many forensic recordings are not made with the highest quality equipment and audio formats. Many forensic recordings are now being made with the use of lossy digital compression algorithms which reduce the amount of data used to store the audio file. In many areas of audio forensics, recordings made with the use of lossy compression have a questioned quality and validity. The effects of lossy compression on ENF signals in analog recordings has been studied by Morjaria [5] using the frequency against time analysis method in which visual analysis of spectrograms is used. The results showed that, for most compression formats, the analog signal recorded was not significantly altered by the compression algorithm to the point that a visual analysis of the ENF would no longer be possible. Morjaria had concluded that MP3 did not maintain the ENF signal, that the ENF signal was "destroyed," and that a visual ENF analysis was not possible after conversion to MP3. These conclusions conflict with the results of this study which shows that MP3 algorithms do not have a seriously detrimental effect on ENF signals.

The purpose of the following study is to quantify the effects of lossy compression on ENF signals which were recorded digitally. The method used to examine the audio files is a frequency domain analysis and statistical examination of the differences between the ENF signals. The result will be to show that no forensic analysis based on the electric network frequency should be disregarded in legal proceedings solely for the reason that the audio file had been converted to any of the ten algorithms tested in this study. This study used the western power grid of the United States. The original uncompressed audio files were recorded as part of the National Center for Media Forensics' ENF database. This database, located in Denver, Colorado, is consistent with recommendations set forth by Grigoras et al. [7].

2. Lossy Compression Formats

The ten compression algorithms that were tested in this experiment were A-law, mu-law, DVI ADPCM, Microsoft ADPCM, high quality MP3 with variable bit-rate, low quality MP3 with variable bit-rate, MP3 with constant bit-rate, high quality Windows Media Audio (WMA) with constant bit-rate, low quality WMA with constant bit-rate, and WMA with variable bit-rate.

The original uncompressed pulse code modulation (PCM) audio files of the ENF used for this experiment had a sample rate of 8 kHz and a 16 bit depth. Therefore, the bit-rate of these original audio files was 128 kilobits per second (kbps). They are saved with .WAV file extensions.

A-law and mu-law (or µ-law) are standard compression algorithms used in telecommunications. Mu-law is used mainly in North America and Japan; A-law is more prevalent in the rest of the world and is the standard in Europe. They are companding algorithms which decrease the dynamic range of the audio file. A-law has a slightly lower dynamic range than mu-law. These algorithms are used because linear digital encoding is inefficient with speech signals. By reducing the dynamic range and increasing the signal to noise ratio, the efficiency of coding is improved and quantization error is reduced. The result is a smaller number of bits used to transmit an intelligible speech signal. The companding component of these algorithms can be applied in the analog domain by using an amplifier with non-linear gain. If telecommunications are transmitted between an A-law network and a mu-law network, the A-law algorithm is used. Both are saved with .WAV file extensions. Various files with .WAV file extensions are differentiated by the header data. A-law and mu-law are also used in some .AU audio file formats created by Sun Microsystems (other encodings are also used in the .AU format including PCM and ADPCM). A typical 8 kHz A-law or mu-law audio file is reduced to 8-bits and has a bit-rate of 64 kbps. Audio files converted to these formats result in files 50% the size of the original PCM audio file.

Two variations of adaptive differential pulse code modulation (ADPCM) were tested: Microsoft ADCPM and DVI ADPCM. These two algorithms both save the data with a .WAV file extension. ADPCM algorithms allow for a varied quantization level. The goal of the varied quantization level is to use a smaller bandwidth to achieve similar signal to noise ratios as larger bandwidths. When encoding from PCM, ADPCM calculates the differences between samples and stores those values while making predictions about the final audio file. Upon decoding, the prediction is combined with the quantized differences to create a reconstructed signal. With lower sample rates, distortion in high frequencies of ADPCM audio files becomes audible, but this is not a problem with 44.1 kHz or higher sample rates. In telephony, ADPCM is sometimes combined with the A-law or mu-law algorithms to create 4 bit ADPCM samples from the A-law or mu-law samples. ADPCM is also used in Voice over IP communications. A typical Microsoft ADPCM audio file uses only 4 bits per sample and has a bit-rate of 32 kbps. The Microsoft ADPCM algorithm used in this experiment was multiple pass and had a large block size. The result was a compression ratio of 3.91:1 and a bit-rate of roughly 32.7 kbps. The DVI ADPCM algorithm used exactly 4 bits per sample and had a bit-rate of 32 kbps. Audio files converted to Microsoft ADPCM resulted in files that were approximately 21% the size of the original PCM audio files and audio files converted to DVI ADPCM yield files approximately 19% the size of the original PCM audio files.

MPEG-2 Audio Layer 3, or MP3, is a compression algorithm designed by the Moving Picture Experts Group as part of the MPEG-1 and MPEG-2 standards. MP3 is arguably the most common form of lossy audio compression in the world. MP3 algorithms work by using psychoacoustic properties, reducing the accuracy of portions of the signal that are deemed less relevant. High frequencies, for example, are nearly eliminated because they are out of the range of most humans' hearing. This is called perceptual encoding. Psychoacoustic models are provided in the MPEG-1 standard, but precise specifications for the encoder are not included. Those implementing the standard were to create their own encoders to meet the psychoacoustic models. There are now a wide variety of MP3 encoders available. For this experiment, an MP3PRO algorithm was used which uses a small amount of extra data other MP3 algorithms don't use to help in reconstructing higher frequencies and can therefore use smaller overall bit-rates that achieve comparable quality as algorithms with higher bit-rates. The audio files are saved in a .MP3 file. Three settings of this algorithm were tested. The first was a constant bit-rate version in which the same bit-rate is used for the entire audio file. The compression ratio was 16:1 and the bit-rate was approximately 8 kbps. Audio files converted with this algorithm yield files approximately 6% the size of the original PCM audio file. Two MP3 settings with variable bit-rate were used: the highest and lowest quality settings for variable bit-rate MP3. With variable bit-rate encoding, more complex signals are encoded with a higher bit-rate than less complex signals. The highest quality setting had a bit-rate that ranges from 75-120 kbps. ENF audio files converted with this highest quality setting yielded files approximately 9% the size of the original audio files. The lowest quality setting had a bit-rate that ranged from 40-50 kbps. ENF audio files converted with this lowest quality setting yielded files approximately 6% the size of the original PCM audio files.

Windows Media Audio, or WMA, is a lossy audio compression algorithm designed by the Microsoft Corporation. There are four variations of WMA codecs. The first is the original WMA compression algorithm known simply as WMA which was first created in 1999 though it has been revised since that time. WMA operates on similar principles as MP3 in that it uses perceptual encoding and psychoacoustics to determine which components of the audio content are less relevant for human hearing. It also can be applied with both constant bit-rate and variable bit-rate. The second is WMA Pro, which supports multi-channel audio and higher resolution audio. A lossless version of WMA was created to compress audio data without losing audio quality. And the fourth codec is WMA Voice, which was created to accurately capture human speech. Version 9.2 of the original WMA codec was used for this experiment. The audio files are saved with a .WMA file extension. Three settings of this algorithm were tested in this experiment. The variable bit-rate setting resulted in files approximately 7% the size of the original PCM audio file and the lowest quality constant bit-rate setting which used 5 kbps also resulted in files approximately 7% the size of the original PCM audio file. The highest quality constant bit-rate setting used 8 kbps and resulted in files approximately 6.5% the size of the original PCM audio file.

3. Methodology

3.1 Processes

The goal of the following process was to create ENF audio files which would be identical to the original files other than that they were processed with a lossy compression algorithm. These compressed files could then be compared to the original to determine the effect that the lossy compression algorithms had on the ENF signal. One hundred test samples were used for each of ten compression algorithms. To ensure that the test samples were unique, one hundred different hours of ENF audio files were used from five different months.

Audio files of the ENF were used from the ENF database at the National Center for Media Forensics in Denver, Colorado. The database operates by reducing the voltage of the electric current and recording it directly as an audio signal. The original audio files were each one day in length. Each of these one day audio files was then converted and saved with the ten different lossy compression algorithms referred to in the previous section using Adobe Audition. Any additional audio samples added to the start of an audio file by the compression algorithm were removed to ensure that the compressed audio files' ENF signal was in phase with the original files' ENF signal. Additional audio samples would throw off later statistical calculations.

The twenty-four hour compressed and uncompressed audio files were divided into hours. Twenty hours were used from each of five days, the first day of each of five consecutive months. The result was 1,100 audio files: ten compressed audio files of different formats for each of one hundred hours and the original one hundred uncompressed hours.

The audio files were then prepared for an ENF analysis; they were down-sampled from their original sampling frequency of 8 kHz to 360 Hz and a band-pass filter was applied from 55 Hz to 65 Hz (100% amplitude at 60 Hz, linearly reduced to 0% amplitude at 55 Hz and 65 Hz). This band pass filter ensured that the only information examined was the ENF signal. For each of the 1,100 audio files, the ENF was then calculated at one second intervals using the average frequency with the maximum magnitude for each second and the frequencies were then saved as a vector (a series of values: one ENF value per second) in a text format. During this process, figures were produced representing the frequency variations of ENF over time. (These figures allow for a visual analysis of the ENF to be conducted.)

Finally, calculations were made to find the statistical differences between the ENF vectors of compressed audio files against the vector for the original audio files. These calculations included mean quadratic differences and correlation coefficients between the original and compressed audio files. The correlation coefficients were also computed with mean subtraction (mean subtraction refers to the average value of a frequency vector being subtracted from every value in that vector before a correlation coefficient calculation is made; this allows for subtle differences between the vectors to be made more apparent). *Higher* correlation coefficients show a higher degree of similarity to the original uncompressed audio file, whereas *lower* mean quadratic differences show a higher degree of similarity to the original uncompressed audio file. A correlation coefficient value of one (1) is the maximum value for a correlation coefficient and shows that the two vectors are identical. A mean quadratic difference value of zero (0) is the minimum value for a mean quadratic difference and shows that the two vectors are identical. The mean values and standard deviations of the correlation coefficients (with and without mean subtraction) and mean quadratic differences were also calculated for each format. The mean value calculations allow for an algorithm's overall degradation of the ENF to be generalized, whereas the standard deviation calculations show the range of effects that an algorithm can have on the ENF signal.

Calculations were also made to find the statistical difference between the compressed formats and three controls. The first control used was to compare the PCM audio file's vector with the previous hour's PCM frequency vector. The second control was to calculate the correlation coefficients with mean subtraction and mean quadratic differences between all audio files of a compressed format and all the other audio files of that format. The third control was to calculate the correlation coefficients with mean subtraction and mean quadratic differences between all the audio files of a compressed format and every other hour's PCM audio file. The purpose of the three controls is to show that it would be extremely unlikely to produce high correlation coefficients or low mean quadratic differences when comparing any two hours' PCM vectors, any two hours' compressed vectors, or any compressed hour with any other hour's PCM vector. If the controls did not show that matching hours produce higher correlation coefficients or lower mean quadratic differences than non-matching hours, then the study would not be relevant.

3.2 Formulas

The formula for correlation coefficients (*CC*), shown here with mean subtraction, is as follows where *x* and *y* are vectors being compared against each other and *xm* and *ym* are the mean values of the vectors:

$$CC = \frac{\sum_{k=1}^{N}(x_k - xm)(y_k - ym)}{\sqrt{\sum_{k=1}^{N}(x_k - xm)^2}\sqrt{\sum_{k=1}^{N}(y_k - ym)^2}}$$

The formula for mean quadratic difference (*MQD*) is as follows where *x* and *y* are vectors being compared against each other:

$$MQD = \log\left(\frac{1}{N}\sum_{k=0}^{k=N}(x_k - y_k)^2\right)$$

To find the mean values (μ) of all correlation coefficients or mean quadratic differences for an algorithm where *x* is a vector containing all the values of either correlation coefficients or mean quadratic differences, the following formula was used:

$$\mu = \frac{\sum_{i=1}^{N} x_i}{N}$$

To find the standard deviation (σ) of all correlation coefficients or mean quadratic differences for an algorithm where μ is the mean of all values for either correlation coefficients or mean quadratic differences and *x* is a vector containing all the values of either correlation coefficients or mean quadratic differences, the following formula was used:

$$\sigma = \sqrt{\frac{\sum_{i=1}^{N}(x_i - \mu)^2}{N}}$$

4. Results

4.1 Correlation Coefficients

The highest correlation coefficients belong to the A-law and mu-law algorithms [Figures 4.1, 4.2]. The A-law algorithm held the single highest mean value of correlation coefficients: 0.999999999982075 [Figures 4.6 and 4.7], but the difference between the mean values for A-law correlation coefficients and mu-law correlation coefficients was negligible (a difference in mean values of approximately 1.399×10^{-13}). The A-law and mu-law algorithms also produced the lowest standard deviation in correlation coefficients [Figure 4.8]. The standard deviation of correlation coefficients was roughly 4.8915×10^{-12} for A-law and 5.1664×10^{-12} for mu-law. The A-law algorithm produced a slightly lower standard deviation of correlation coefficients; again, the difference in standard deviations between the two algorithms was negligible. These two algorithms represent the extreme highs in correlation coefficients, and therefore cause the least signal degradation.

The A-law and mu-law algorithms were followed by the Microsoft ADPCM algorithm, which held the third highest mean value of correlation coefficients: 0.999999999901071 [Figures 4.6 and 4.7] but had the seventh highest standard deviation of correlation coefficients: roughly 5.6584×10^{-11} [Figure 4.8] (the highest quality WMA algorithm with constant bit-rate and all three MP3 algorithms produced less varied results).

The high quality WMA algorithm with constant bit-rate produced the fourth highest average values for correlation coefficients (0.999999999852890) [Figures 4.6 and 4.7], and the sixth lowest standard deviation of correlation coefficients (roughly 4.0223×10^{-11}) [Figure 4.8].

The DVI ADPCM algorithm had the fifth highest mean value of correlation coefficients (0.999999999844249) [Figures 4.6 and 4.7], though it held the eighth highest standard deviation of correlation coefficients (roughly 9.7664×10^{-11}) [Figure 4.8]; it produced more varied results than algorithms with lower average correlation coefficients, much like the Microsoft ADPCM algorithm.

The high quality MP3 algorithm with variable bit-rate held the sixth highest mean value of correlation coefficients (0.999999999752317) and the third lowest standard deviation of correlation coefficients (roughly 2.4344×10^{-11}), followed by the low quality MP3 algorithm with variable bit-rate which held the seventh highest mean value of correlation coefficients (0.999999999741477) and the fourth lowest standard deviation of correlation coefficients (roughly 2.8767×10^{-11}) [Figures 4.6, 4.7, and 4.8]. The MP3 algorithm with constant bit-rate held the eighth highest mean value of correlation coefficients (0.999999999617195) and the fifth lowest standard deviation of correlation coefficients (roughly 3.4487×10^{-11}) [Figures 4.6, 4.7, and 4.8].

Two WMA algorithms produced the two lowest average correlation coefficients [Figure 4.1]. The WMA algorithm with variable bit-rate held the second lowest mean value of correlation coefficients (0.999999997216846) but also produced the highest standard deviation of correlation coefficients (roughly 3.6725×10^{-10}), whereas the low quality WMA algorithm with constant bit-rate held the lowest mean value of correlation coefficients (0.999999997216107) and the second highest standard deviation (roughly 3.6706×10^{-10}). For both mean values of correlation coefficients and standard deviation of correlation coefficients, the difference between the WMA algorithm with variable bit-rate and the low quality WMA algorithm with constant bit-rate was negligible (a difference in mean values of approximately 7.389×10^{-13} and a difference in standard deviations of approximately 1.348×10^{-19}). These two algorithms represent the extreme lows in correlation coefficients, and therefore cause the most signal degradation.

When the correlation coefficients were calculated with mean subtraction [Figures 4.3, 4.4, and 4.5], though the compression algorithms' rank remain in the same order for mean values of correlation coefficients [Figures 4.9, 4.10, and 4.11], the standard deviations of correlation coefficients rearrange dramatically [Figure 4.12]. The highest quality WMA algorithm with constant bit-rate moves up from sixth to the third lowest standard deviation of correlation coefficients, the Microsoft ADPCM algorithm moves up from seventh to the fourth lowest standard deviation of correlation coefficients, the highest quality MP3 algorithm with variable bit-rate moves down from third to the fifth lowest standard deviation of correlation coefficients, the lowest quality MP3 algorithm with variable bit-rate moves down from fourth to the sixth lowest standard deviation of correlation coefficients, the DVI ADPCM algorithm moves up from eighth to the seventh lowest standard deviation of correlation coefficients, and the MP3 algorithm with constant bit-rate moves down from fifth to the eighth lowest standard deviation of correlation coefficients.

4.1.1 Correlation Coefficients for First Control

Calculating correlation coefficients for the first control [Figure 4.13], the PCM vector being tested against the previous hours PCM vector, resulted in much lower values than any of the compression algorithms produced when compared against the same hour's PCM vector and a much higher standard deviation of correlation coefficients [Figures 4.13, 4.14, and 4.15]. These differences are far clearer when the correlation coefficient is applied to the first control with mean subtraction [Figures 4.16, 4.17, and 4.18]. For the compression algorithms being tested against the same hour's PCM vector, mean values of correlation coefficients with mean subtraction ranged from the A-law algorithm yielding a 0.999497714578915 to the lowest quality WMA algorithm with constant bit-rate yielding a 0.928355315643604; a range of only 0.071142398935315. The mean value of correlation coefficients with mean subtraction for the first control was 0.108186984019554. Here, the range from the mean value of correlation coefficients with mean subtraction for the lowest quality WMA algorithm with constant bit-rate to the mean value of the control was a larger 0.820168331624050, and the range from the mean value of correlation coefficients for A-law to the mean value of the control was an even larger 0.891310730559361. The highest standard deviation for the correlation coefficients with mean subtraction of the tested algorithms against the same hour's PCM audio file was 0.033566 (lowest quality WMA algorithm with constant bit-rate) and the lowest was 0.000300 (A-law). The standard deviation of the correlation coefficients with mean subtraction for the first control was 0.222028. The lowest values for the correlation coefficients calculated with mean subtraction for the control were approximately -0.49.

For all of the following plots, including mean quadratic difference plots in Section 4.2, the x-axis is a list of algorithms in alphabetical order defined here:

Figures Legend and Abbreviations:

1: A-law (AL)
2: DVI ADPCM (DVI)
3: MP3 with Constant Bit-Rate (MP3C)
4: Highest Quality MP3 with Variable Bit-Rate (MP3H)
5: Lowest Quality MP3 with Variable Bit-Rate (MP3L)
6: Microsoft ADPCM (MSA)
7: mu-law (ML)
8: Highest Quality WMA with Constant Bit-Rate (WMAH)
9: Lowest Quality WMA with Constant Bit-Rate (WMAL)
10: WMA with Variable Bit-Rate (WMAV)
11: First Control: Previous Hour's PCM Vector (CPCM)

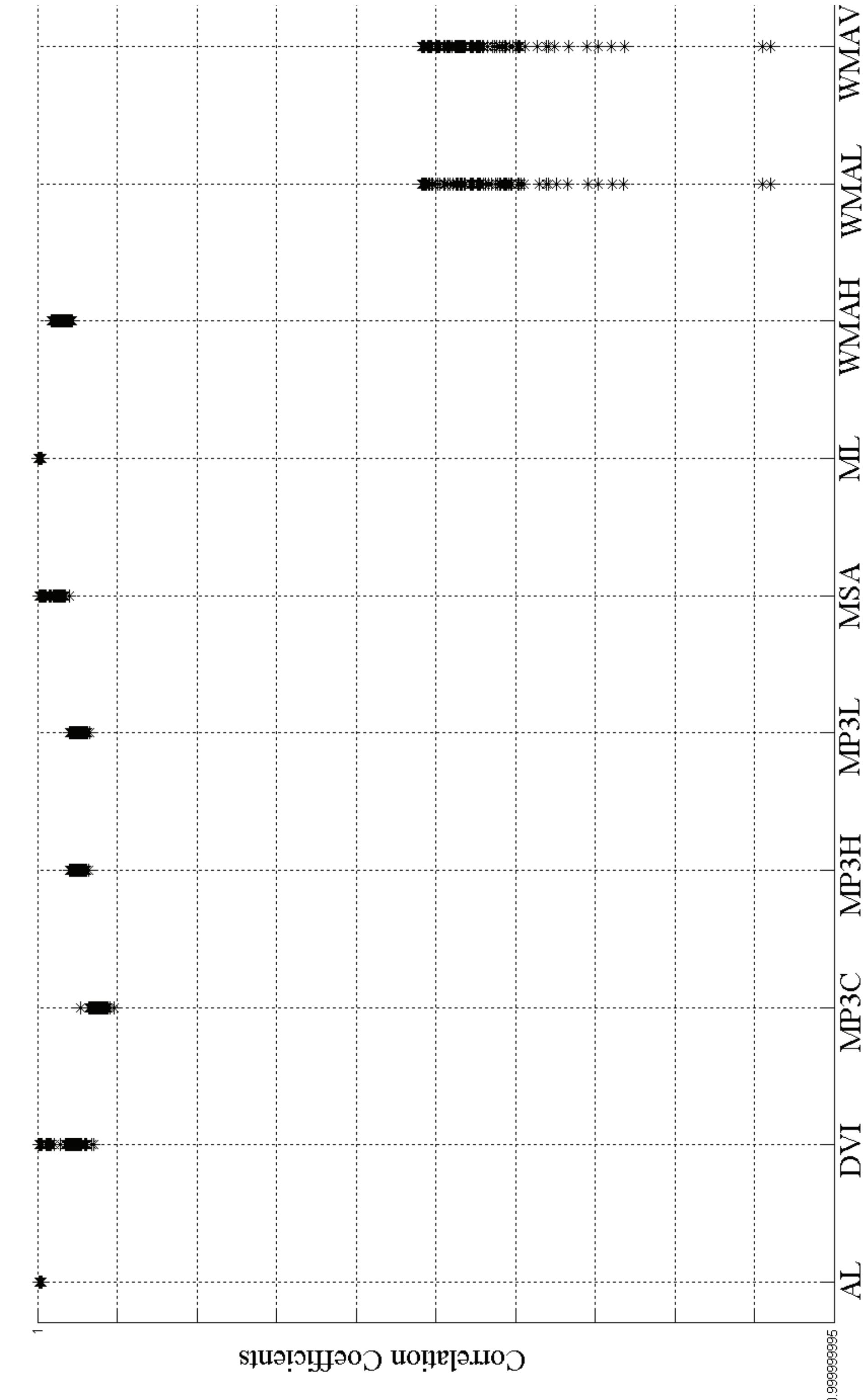

Figure 4.1 Correlation Coefficients

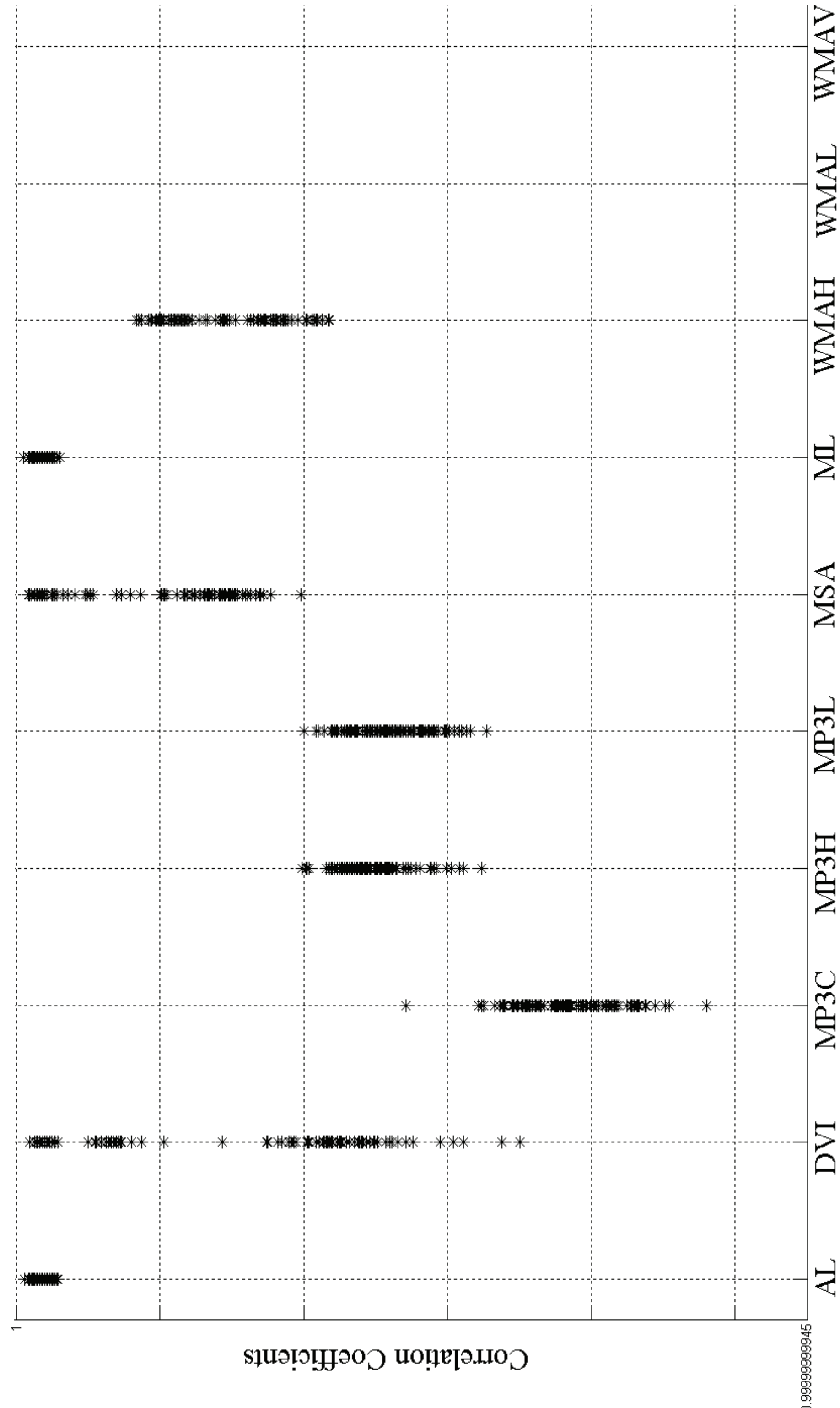

Figure 4.2 Correlation Coefficients (Top 8)

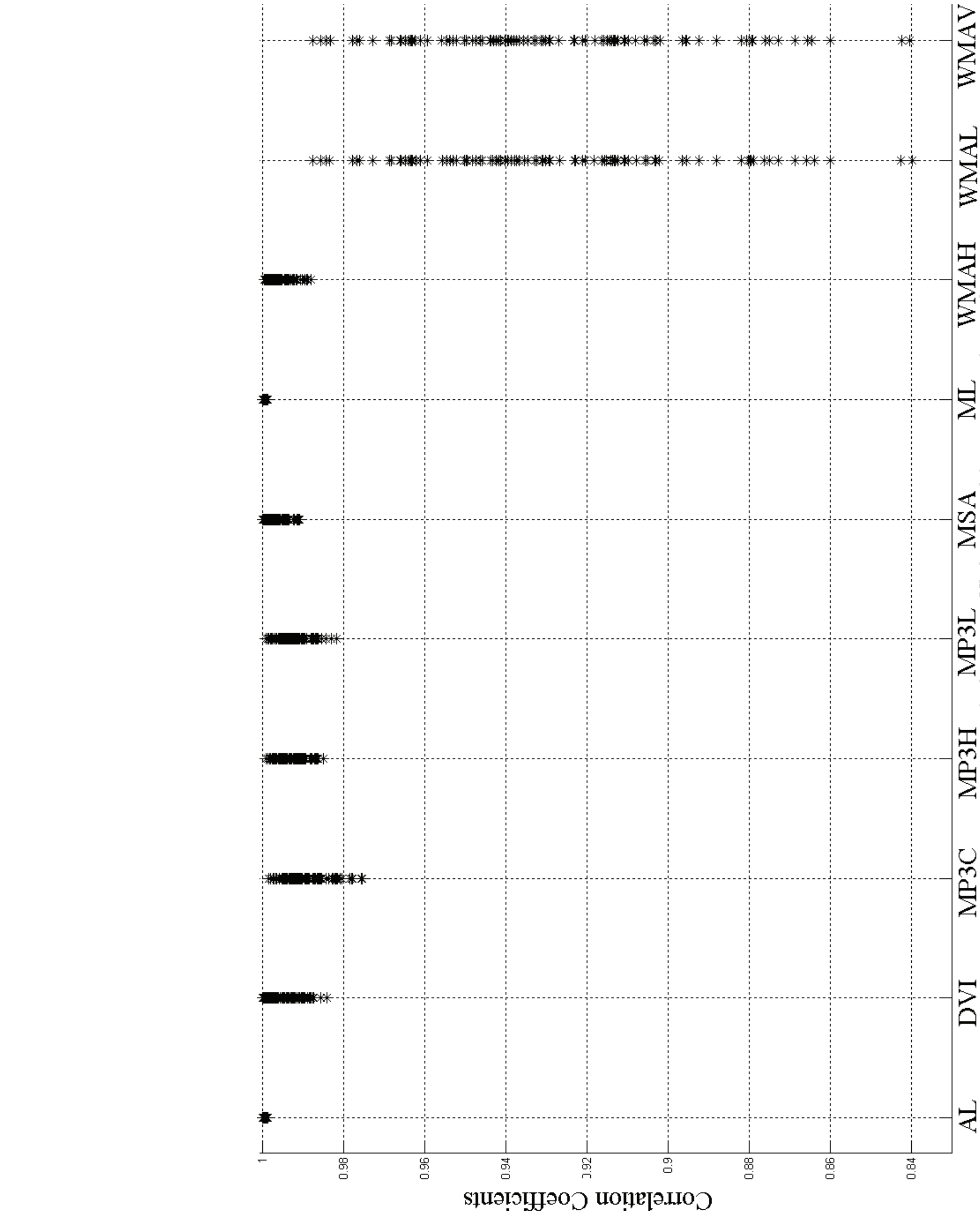

Figure 4.3 Correlation Coefficients With Mean Subtraction

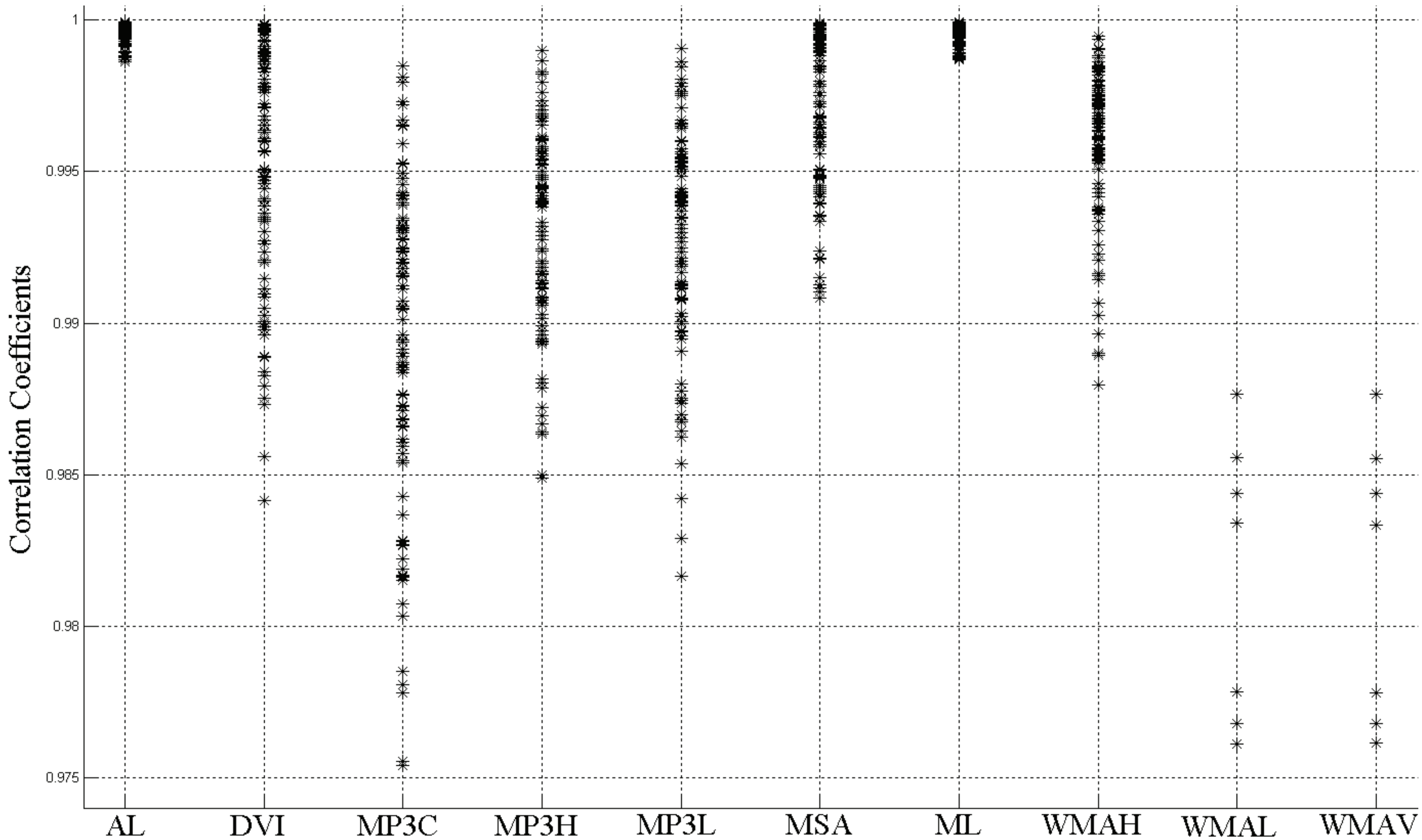

Figure 4.4 Correlation Coefficients With Mean Subtraction (Top 8)

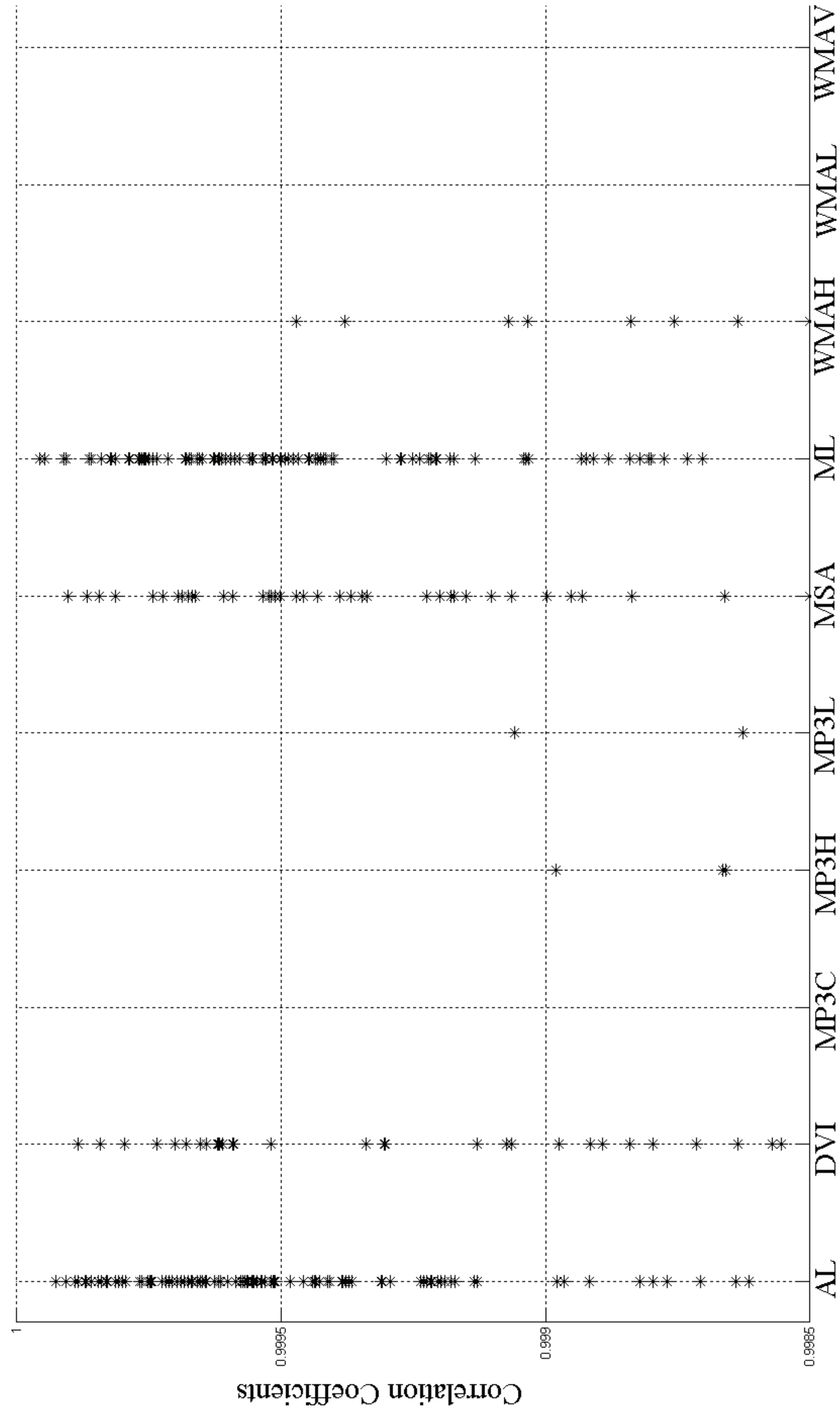

Figure 4.5 Correlation Coefficients With Mean Subtraction (Top 2)

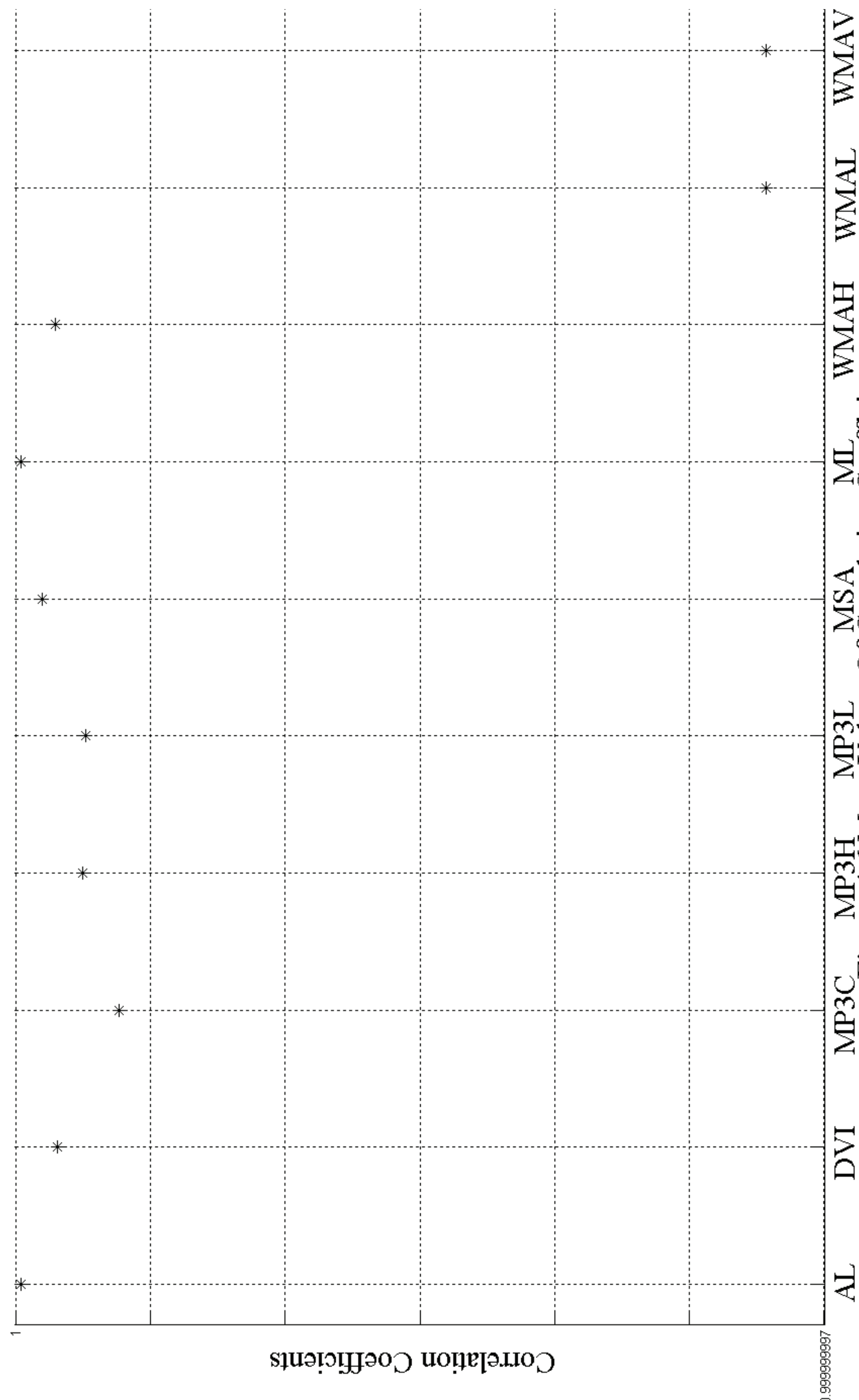

Figure 4.6 Mean Values Of Correlation Coefficients

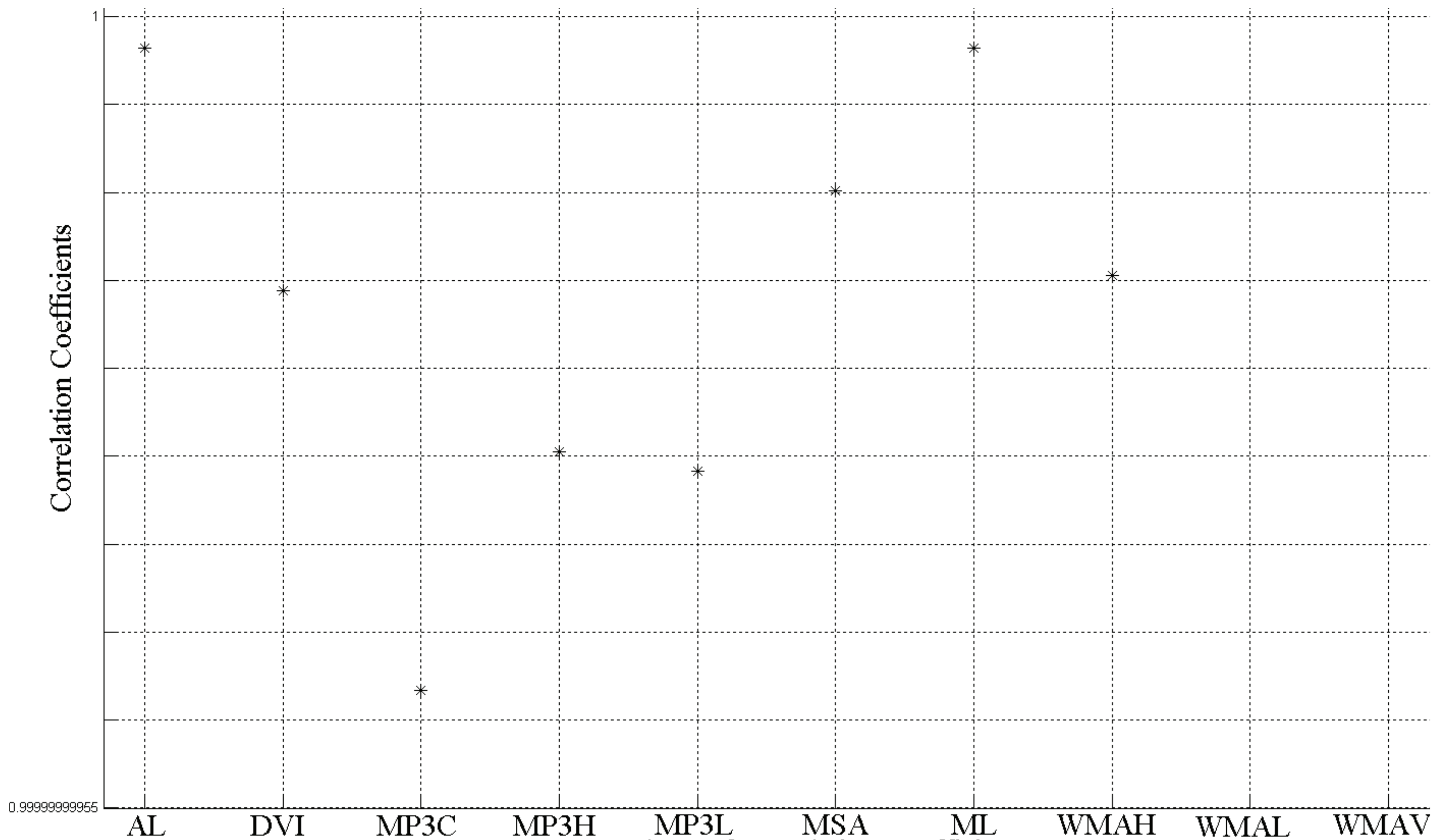

Figure 4.7 Mean Values Of Correlation Coefficients (Top 8)

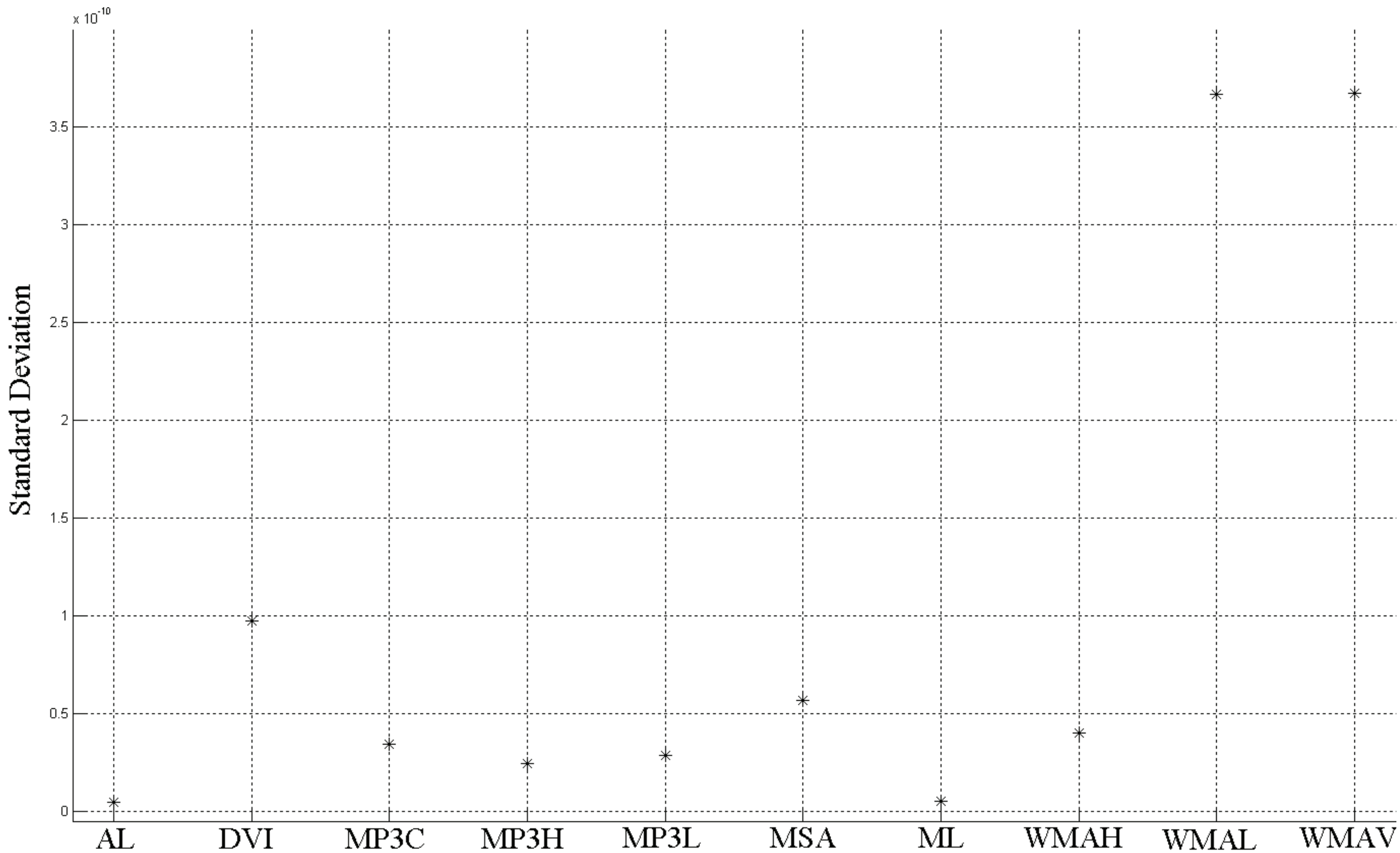

Figure 4.8 Standard Deviation Of Correlation Coefficients

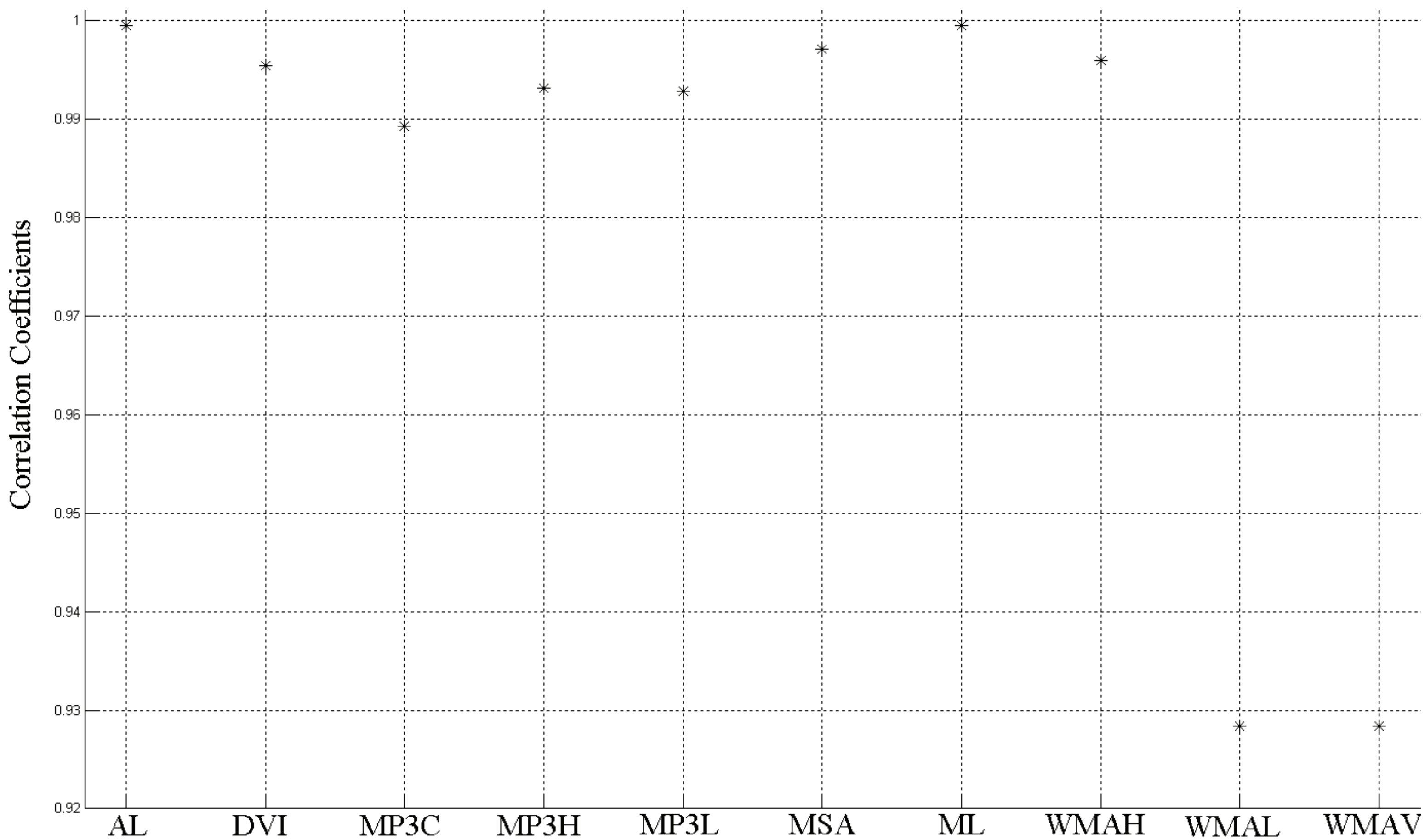

Figure 4.9 Mean Values Of Correlation Coefficients With Mean Subtraction

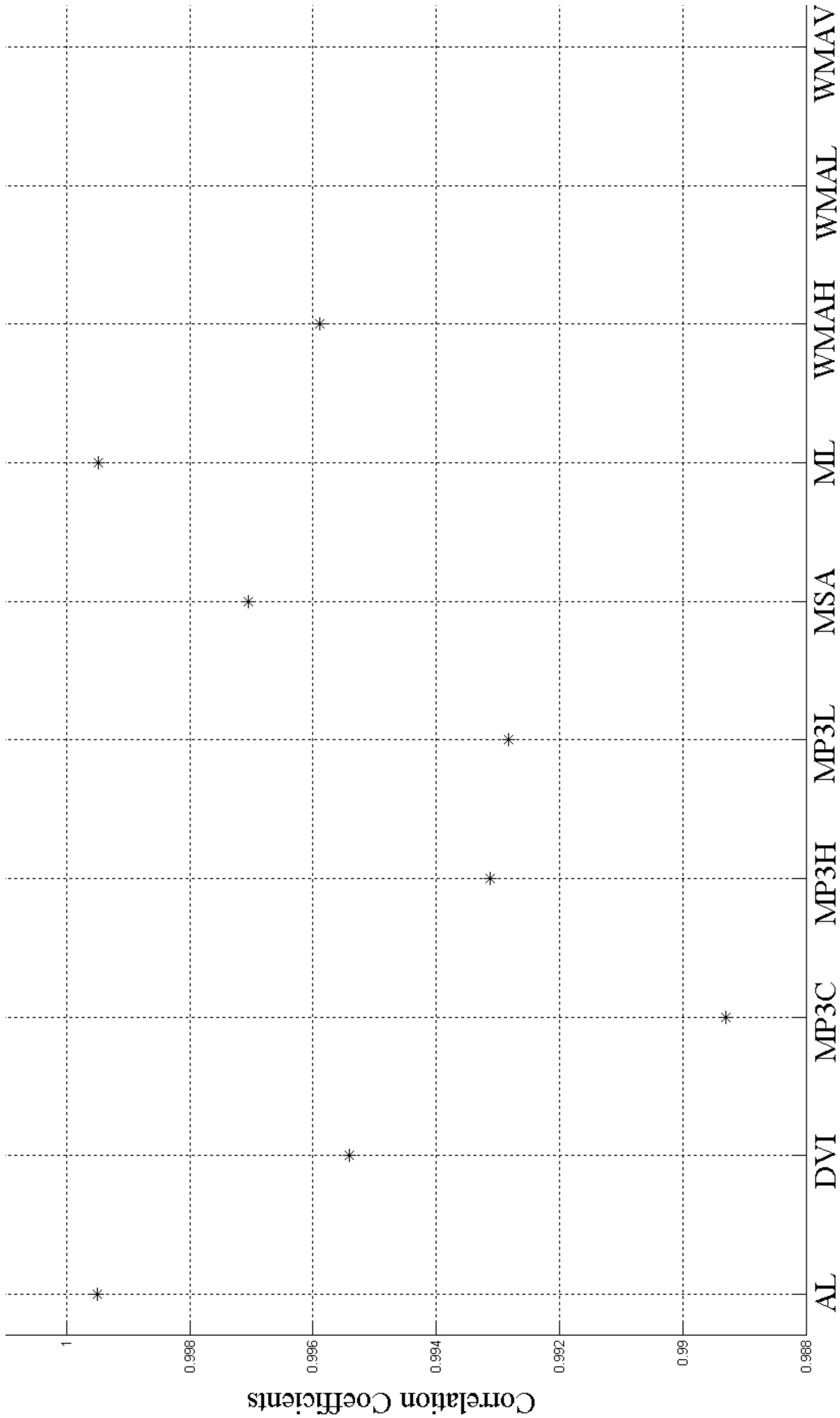

Figure 4.10 Mean Values Of Correlation Coefficients With Mean Subtraction (Top 8)

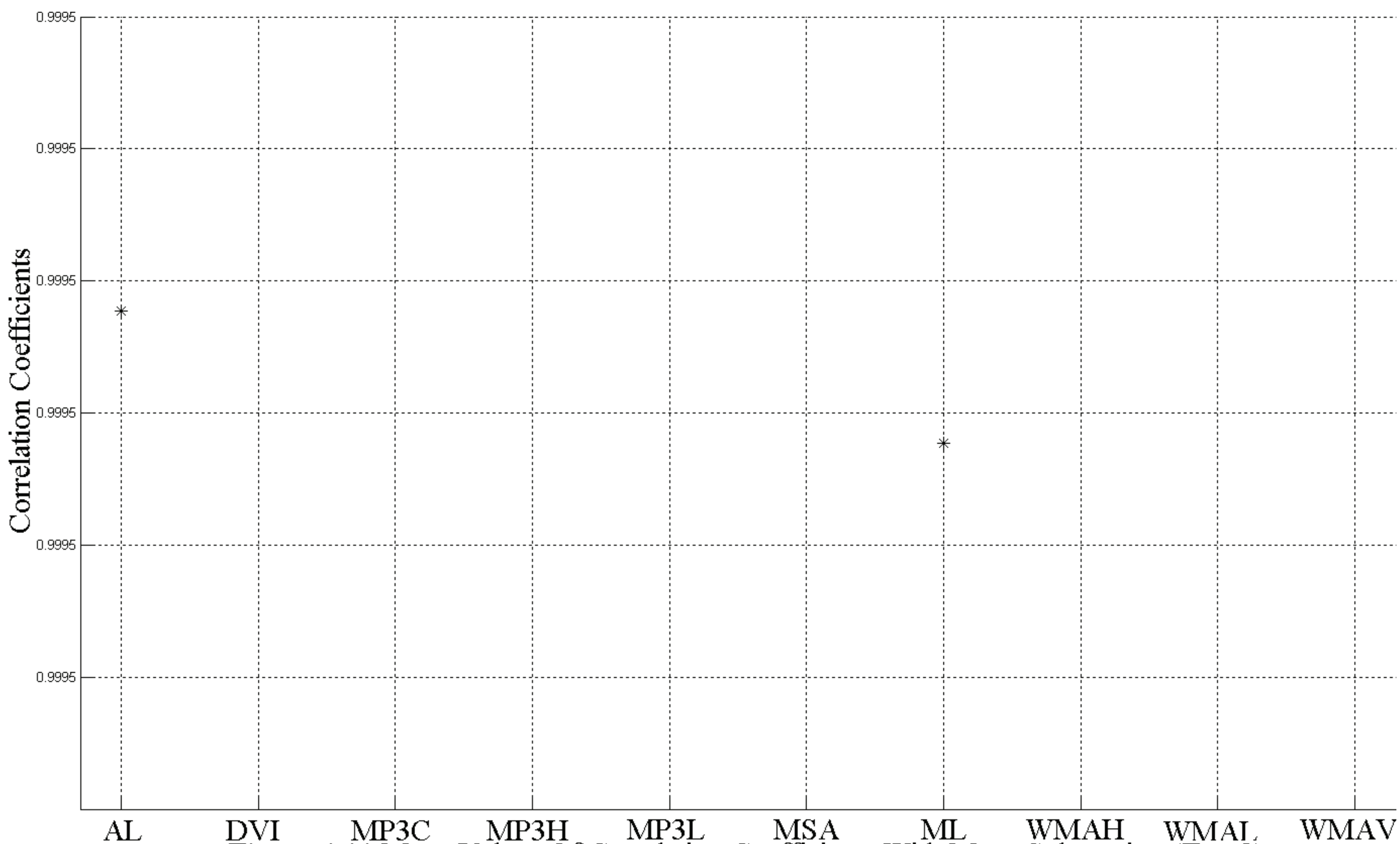

Figure 4.11 Mean Values Of Correlation Coefficients With Mean Subtraction (Top 2)

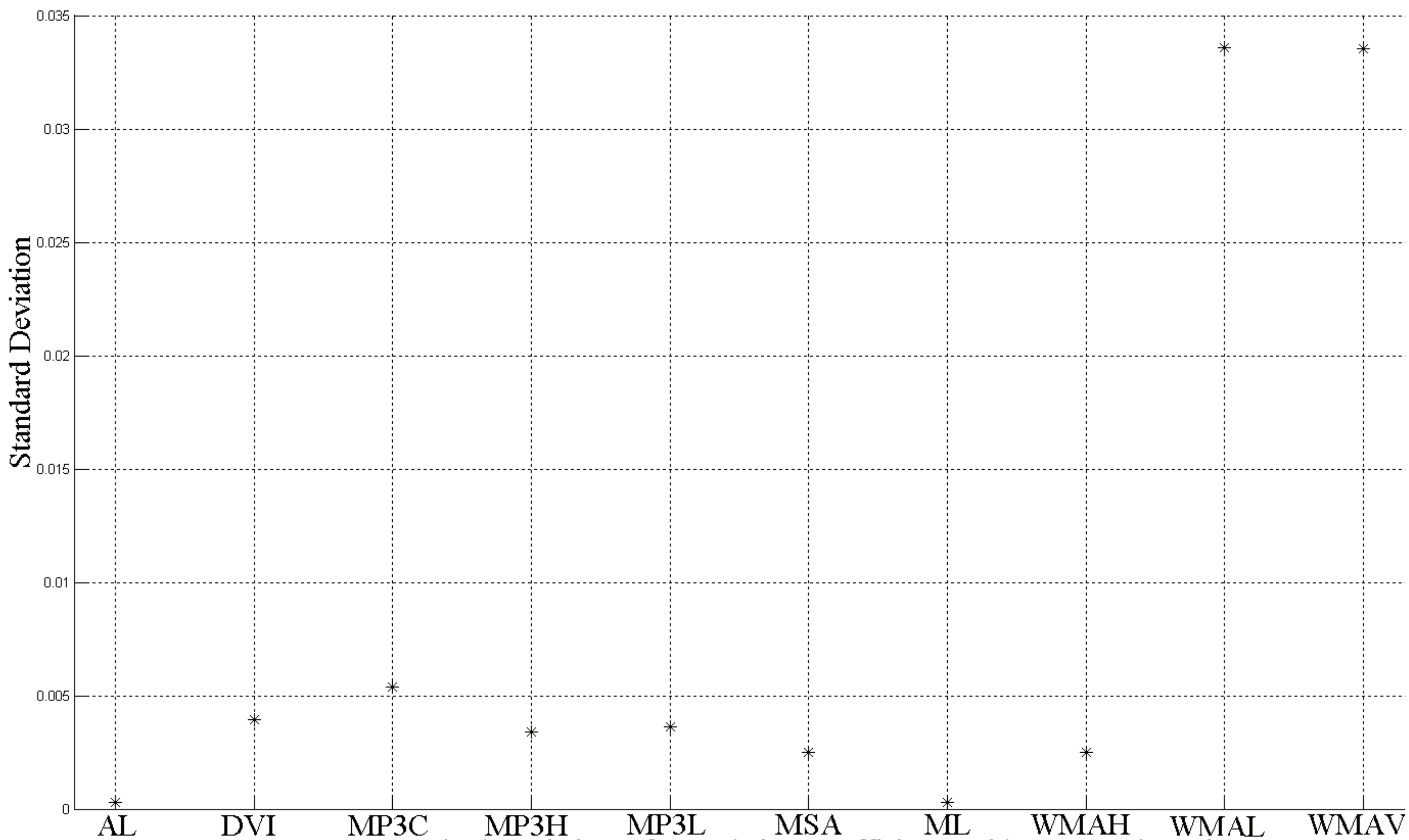

Figure 4.12 Standard Deviation Of Correlation Coefficients With Mean Subtraction

Figure 4.13 Correlation Coefficients Against First Control

Figure 4.14 Mean Values Of Correlation Coefficients Against First Control

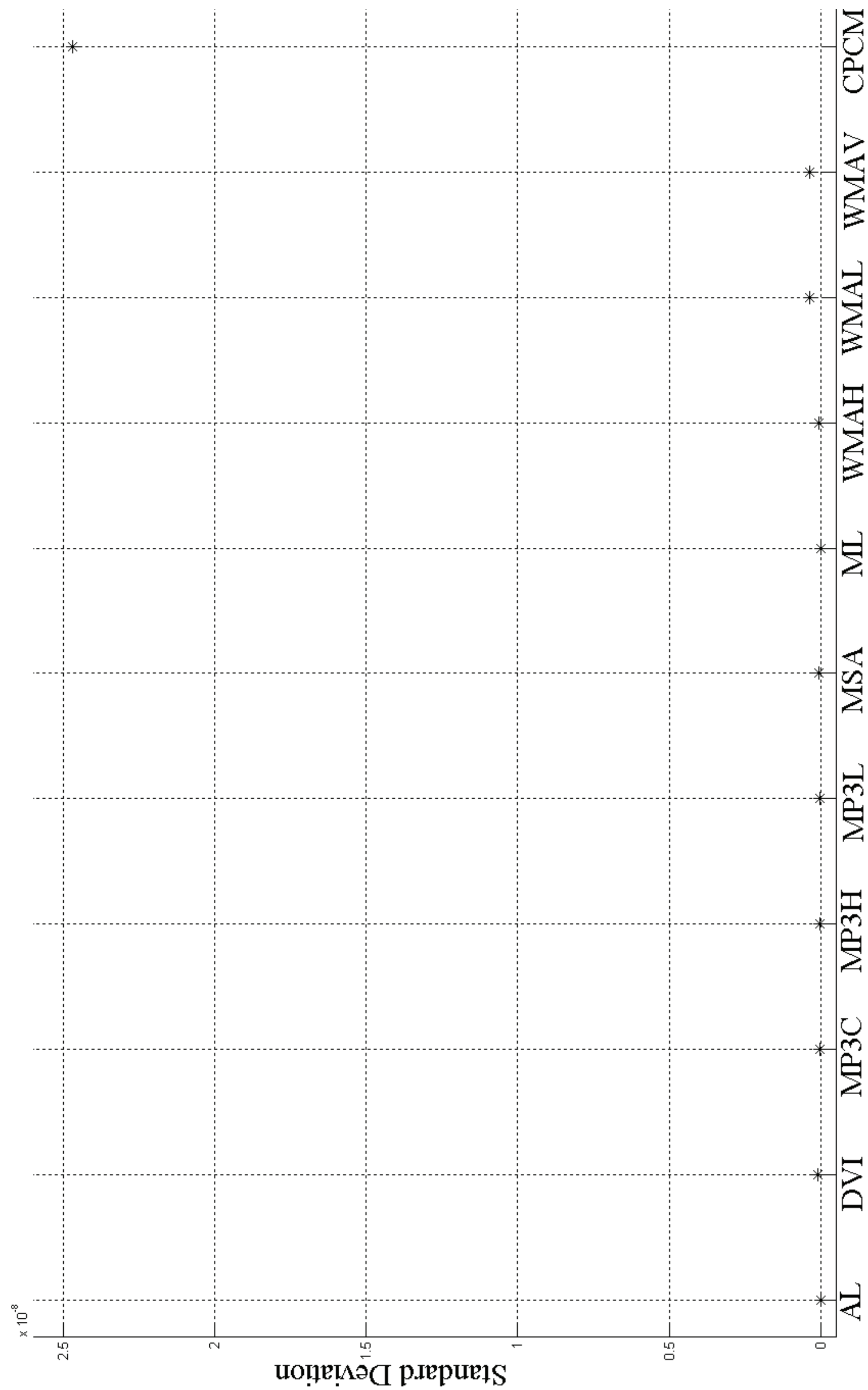

Figure 4.15 Standard Deviation Of Correlation Coefficients Against First Contrtol

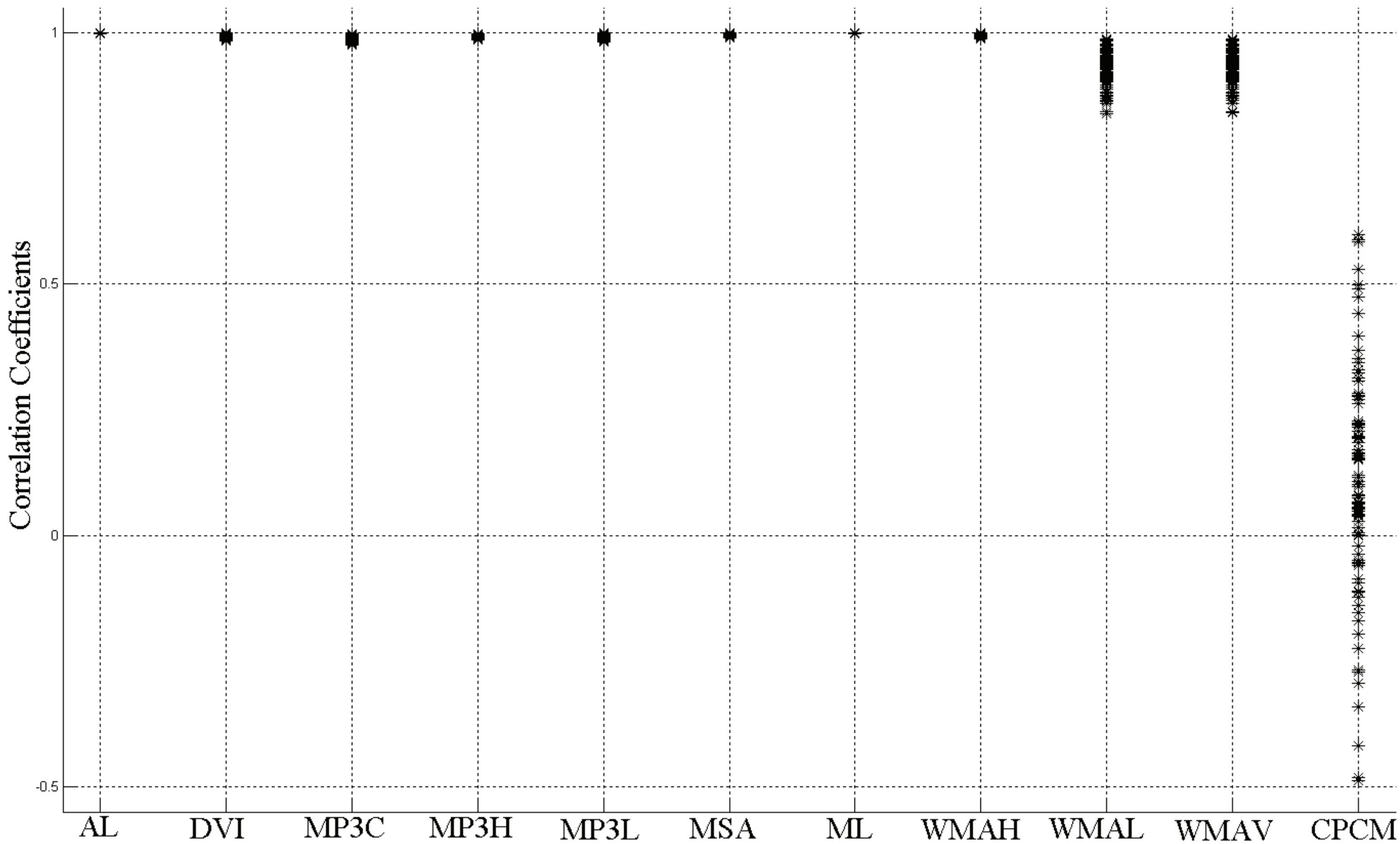

Figure 4.16 Correlation Coefficients With Mean Subtraction Against First Control

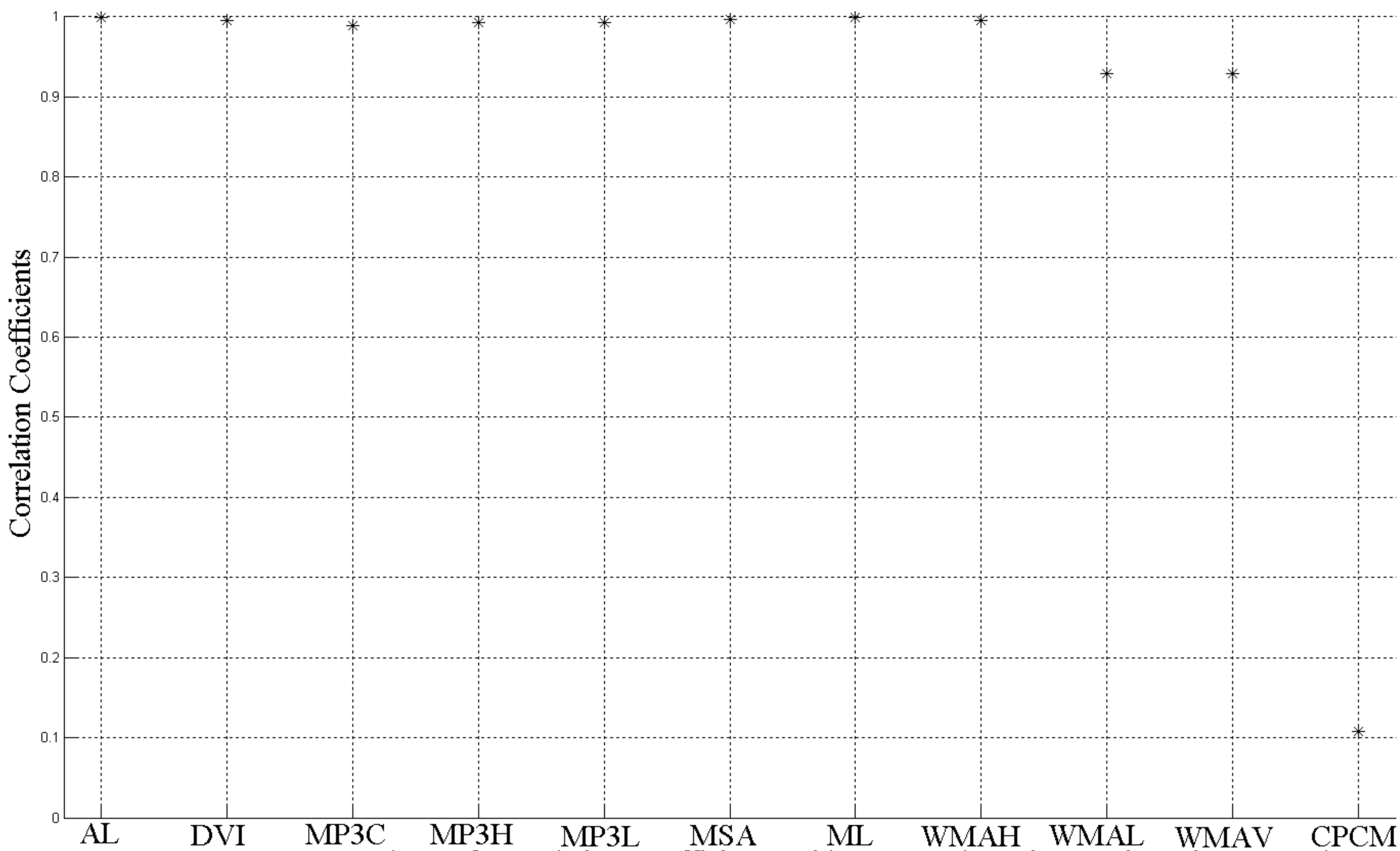

Figure 4.17 Mean Values Of Correlation Coefficients With Mean Subtraction Against First Control

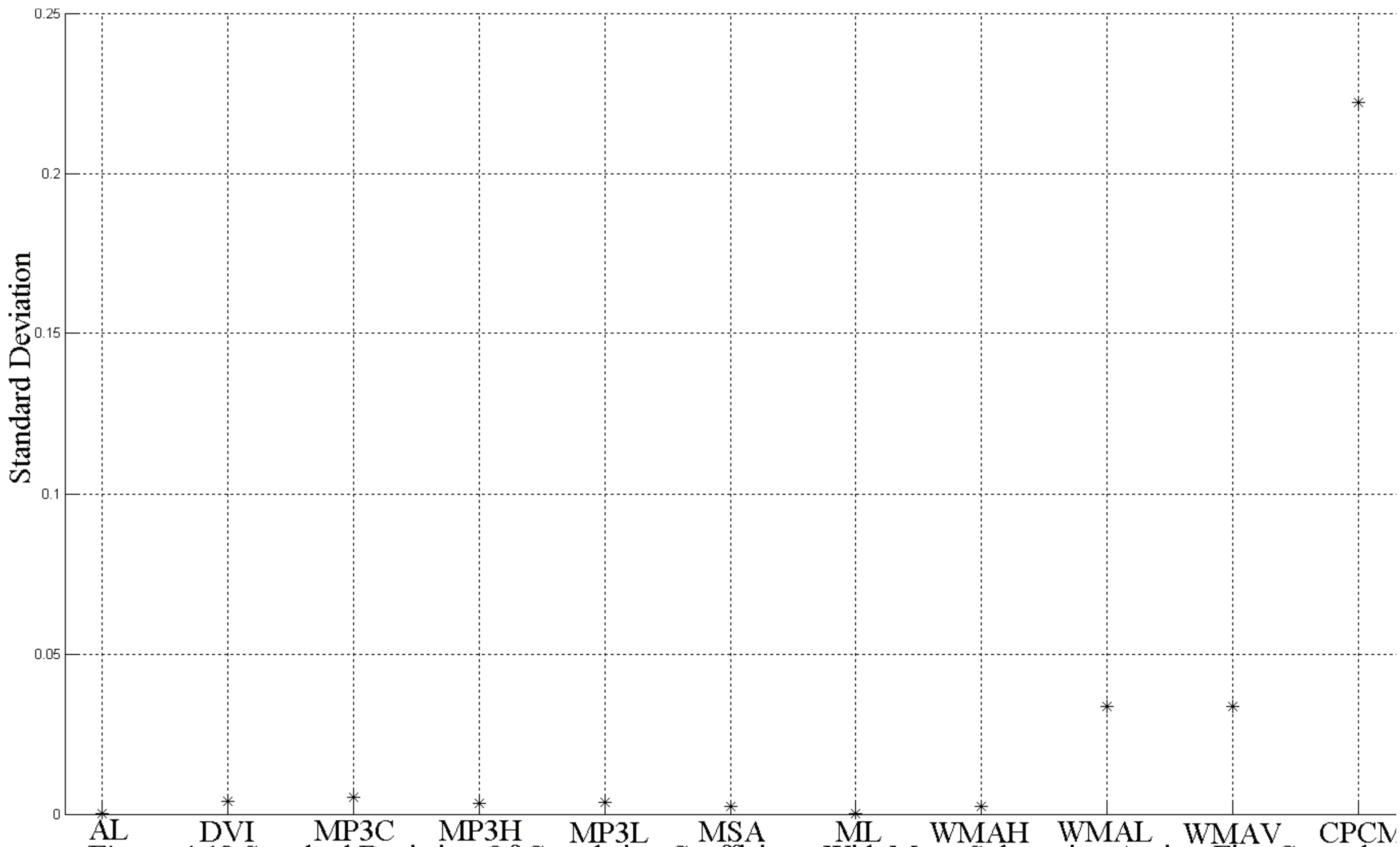

Figure 4.18 Standard Deviation Of Correlation Coefficients With Mean Subtraction Against First Control

4.2 Mean Quadratic Differences

The lowest mean quadratic differences again belonged to the A-law and mu-law algorithms [Figures 4.19, 4.20, and 4.21]. Though the difference in average values for mean quadratic differences between the two algorithms was trivial, the lower value was held by the A-law algorithm. (Average values of mean quadratic differences were roughly 5.9303×10^{-6} for A-law and 5.9471×10^{-6} for mu-law [Figure 4.22].) Much like the correlation coefficients, the mean quadratic differences also showed that the A-law algorithm typically causes the least ENF signal degradation. It should be noted that the mu-law algorithm held mean quadratic difference values both higher and lower than the range of values for the A-law algorithm, therefore having a higher standard deviation meaning that its effect on the ENF signal is slightly less predictable than that of the A-law algorithm. The standard deviation of mean quadratic differences was roughly 8.4485×10^{-7} for A-law and 8.9148×10^{-7} for mu-law [Figure 4.23]. These two algorithms represent the extreme lows in mean quadratic differences, and therefore cause the least signal degradation.

The A-law and mu-law algorithms were followed by the Microsoft ADPCM algorithm, which held the third lowest average mean quadratic differences (1.3248×10^{-5}) [Figure 4.22] and the ninth highest standard deviation of mean quadratic differences (4.7653×10^{-6}) [Figure 4.23]. Also like the correlation coefficients, though its average value for mean quadratic differences was low, showing less average signal degradation, it produced a much higher standard deviation of mean quadratic differences and therefore had a less predictable effect on the ENF signal than other algorithms which had higher mean quadratic differences. The DVI ADPCM algorithm had the fourth lowest average value for mean quadratic differences (1.6406×10^{-5}) [Figure 4.22] but had the single highest standard deviation of mean quadratic differences (6.5584×10^{-6}) [Figure 4.23]. This differs from the correlation coefficients where the highest quality WMA algorithm with constant bit-rate held the fourth highest correlation coefficients -- though the difference between average values for mean quadratic differences is negligible between the DVI ADPCM algorithm and the highest quality WMA algorithm with constant bit-rate (a difference of 5.9126×10^{-7}). The DVI ADPCM algorithm produced mean quadratic difference values much higher and much lower than the range of values for the highest quality WMA algorithm with constant bit-rate, which had a far lower standard deviation of mean quadratic differences. The highest quality WMA algorithm with constant bit-rate then held the fifth lowest average value of mean quadratic differences (1.6998×10^{-5}) [Figure 4.22] and the sixth lowest standard deviation of mean quadratic differences (2.3569×10^{-6}) [Figure 4.23].

The highest quality MP3 algorithm with variable bit-rate held the sixth lowest average value of mean quadratic differences (2.2238×10^{-5}) [Figure 4.22] and the third lowest standard deviation of mean quadratic differences (1.0802×10^{-6}) [Figure 4.23], followed by the lowest quality MP3 with variable bit-rate which held the seventh lowest average value of mean quadratic differences (2.2711×10^{-5}) [Figure 4.22] and the fifth lowest standard deviation of mean quadratic differences (1.2662×10^{-6}) [Figure 4.23]. The MP3 algorithm with constant bit-rate had the eighth lowest average value of mean quadratic differences (2.7652×10^{-5}) [Figure 4.22] and the fourth lowest standard deviation of mean quadratic differences (1.2515×10^{-6}) [Figure 4.23]. Much like the data from the correlation coefficient calculations, the MP3 algorithms had low standard deviations of mean quadratic differences and therefore had a more predictable effect on the ENF signal than some of the algorithms with lower average values of mean quadratic differences.

The two WMA algorithms which produced the extreme lows for correlation coefficients also produced the extreme highs for mean quadratic differences. The WMA algorithm with variable bit-rate produced the second highest average value of mean quadratic differences (7.4501×10^{-5}) [Figure 4.22] and the third highest standard deviation of mean quadratic differences (4.5878×10^{-6}) [Figure 4.23]. The lowest quality WMA algorithm with constant bit-rate held the highest average value for mean quadratic differences (7.4512×10^{-5}) [Figure 4.22] and the fourth lowest standard deviation of mean quadratic differences (4.5860×10^{-6}) [Figure 4.23]. Much like the correlation coefficients, between these two WMA algorithms, the algorithm with the higher average value of mean quadratic differences and therefore less signal degradation produced the higher standard deviation of mean quadratic differences and was therefore less predictable. Also, as was the case for the correlation coefficients, the difference between these two algorithms in both average value of mean quadratic differences and in standard deviation of mean quadratic differences was trivial.

4.2.1 Mean Quadratic Differences for First Control

Calculating mean quadratic differences for the first control, the PCM vector being tested against the previous hours PCM vector, resulted in much higher values than any of the compression algorithms produced when compared against the same hour's PCM vector and a much higher standard deviation of mean quadratic differences [Figures 4.24, 4.25, and 4.26].

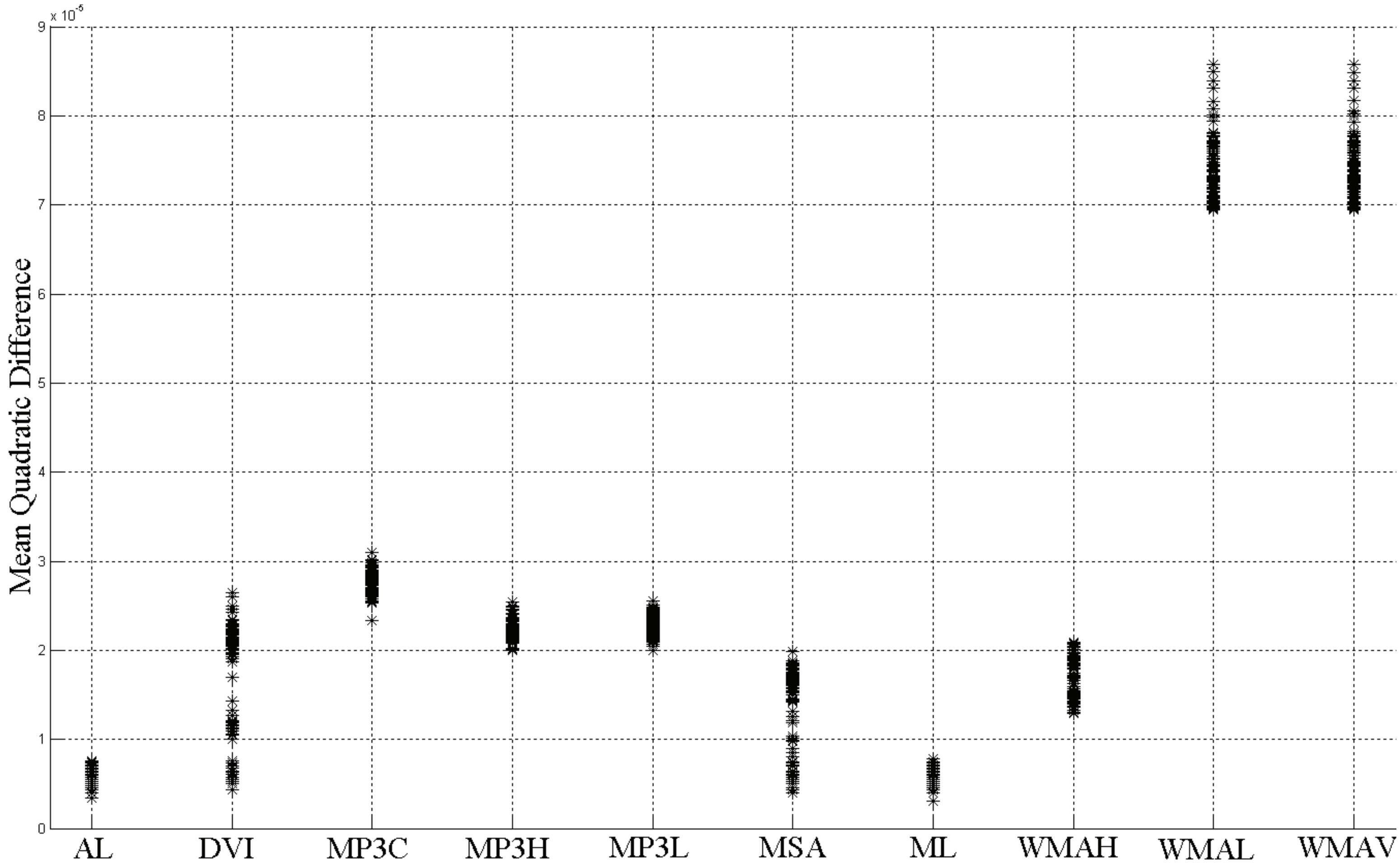

Figure 4.19 Mean Quadratic Differences

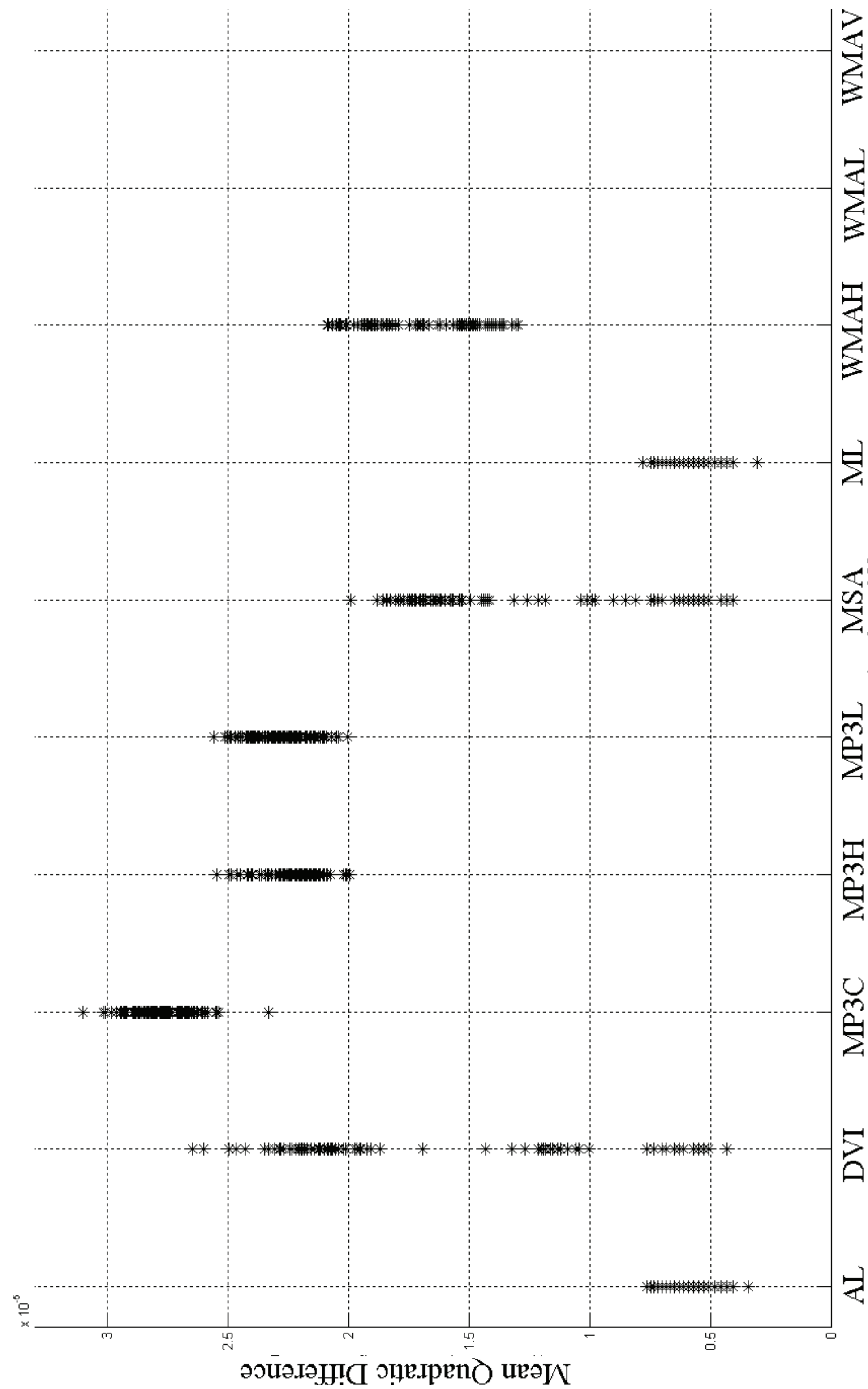

Figure 4.20 Mean Quadratic Difference (Top 8)

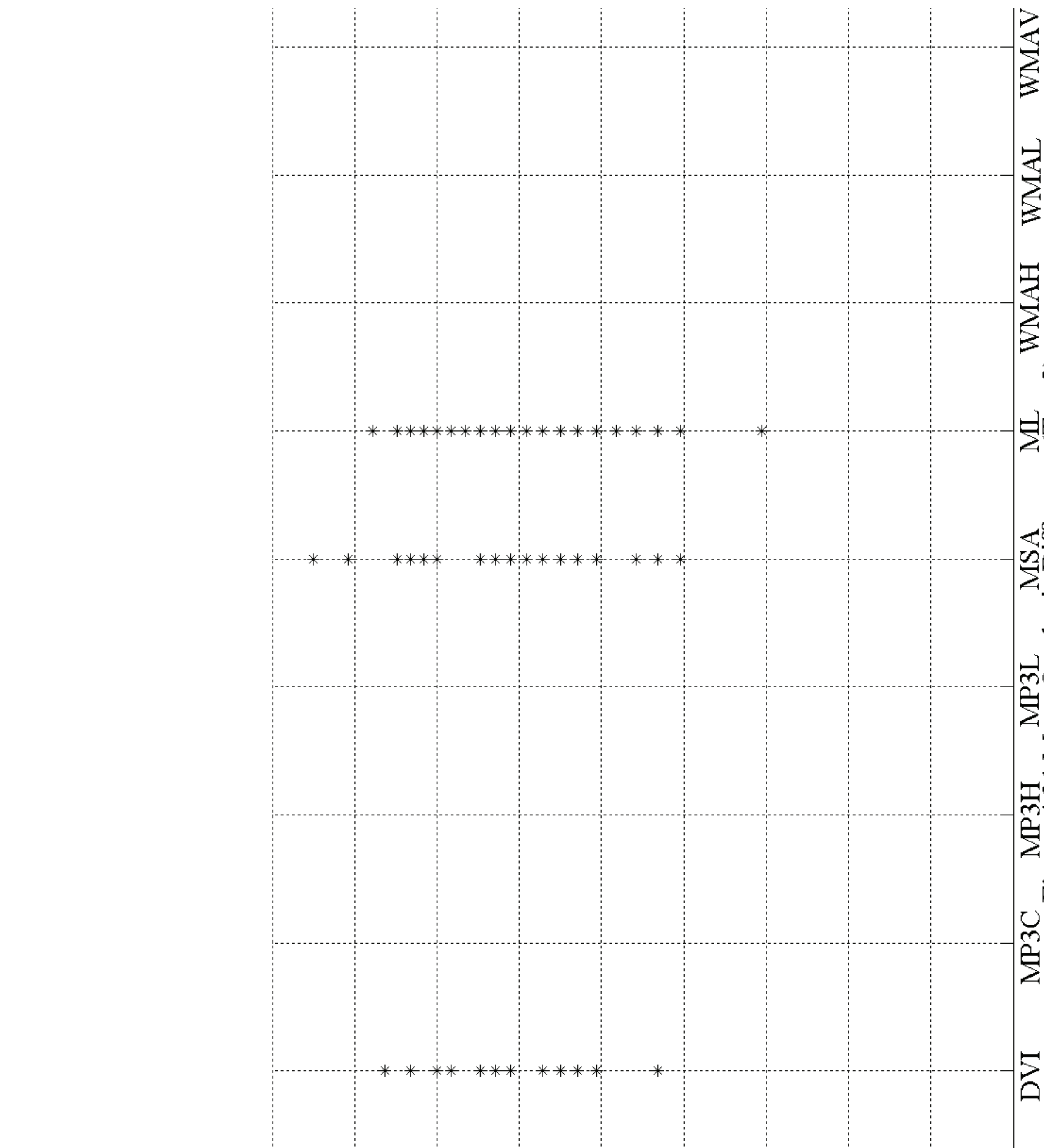

Figure 4.21 Mean Quadratic Difference (Top 2)

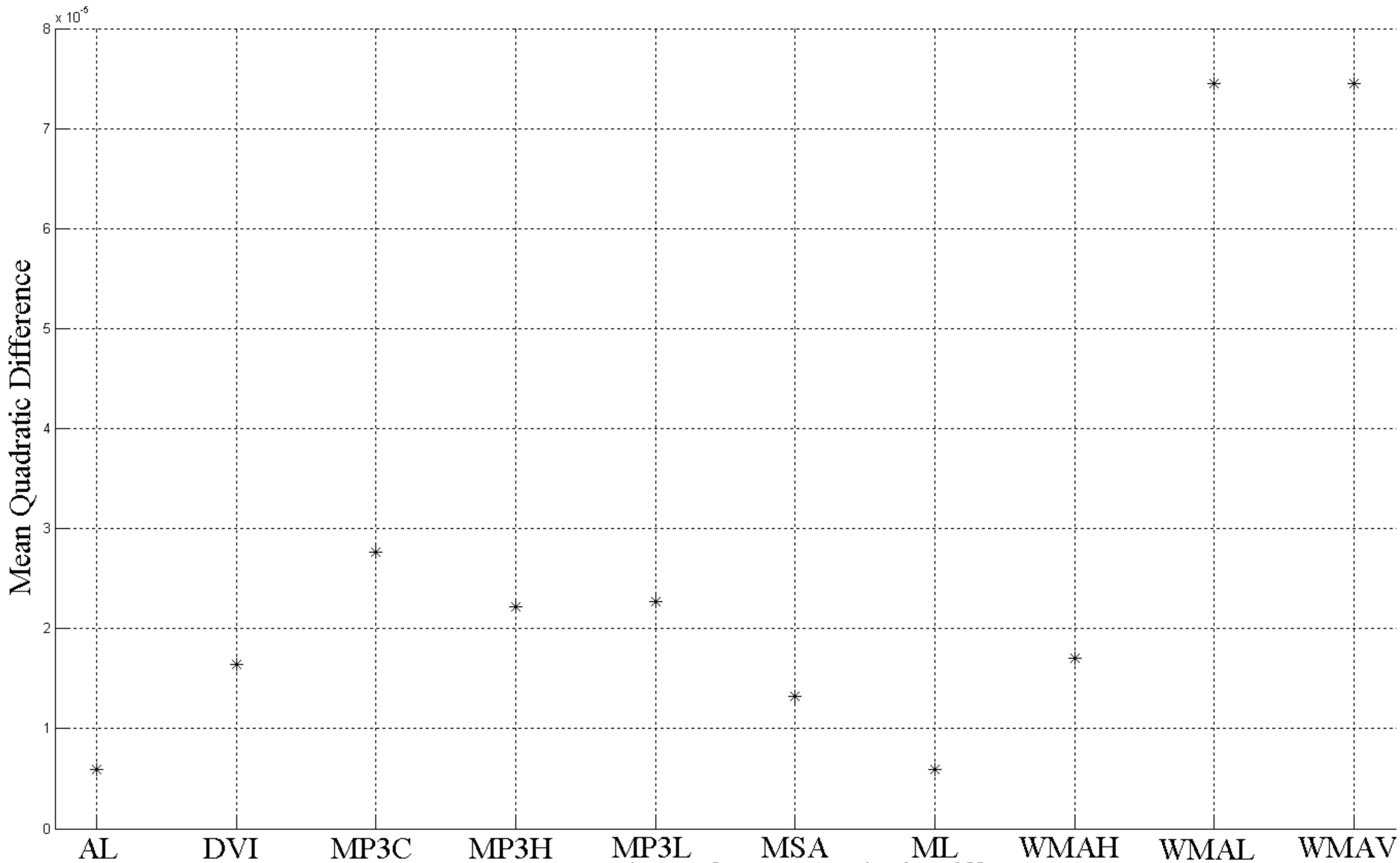

Figure 4.22 Mean Values Of Mean Quadratic Differences

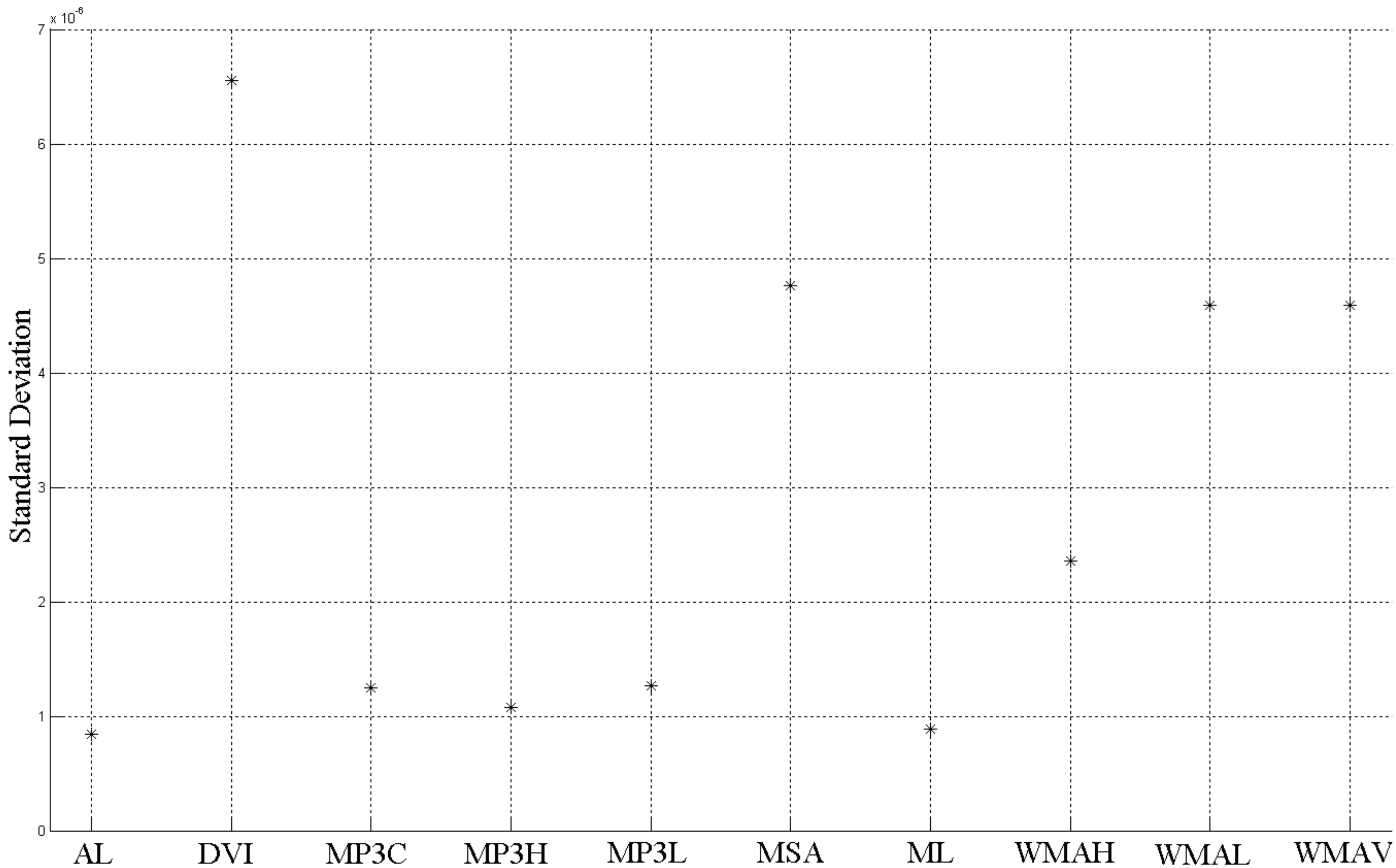

Figure 4.23 Standard Deviation Of Mean Quadratic Differences

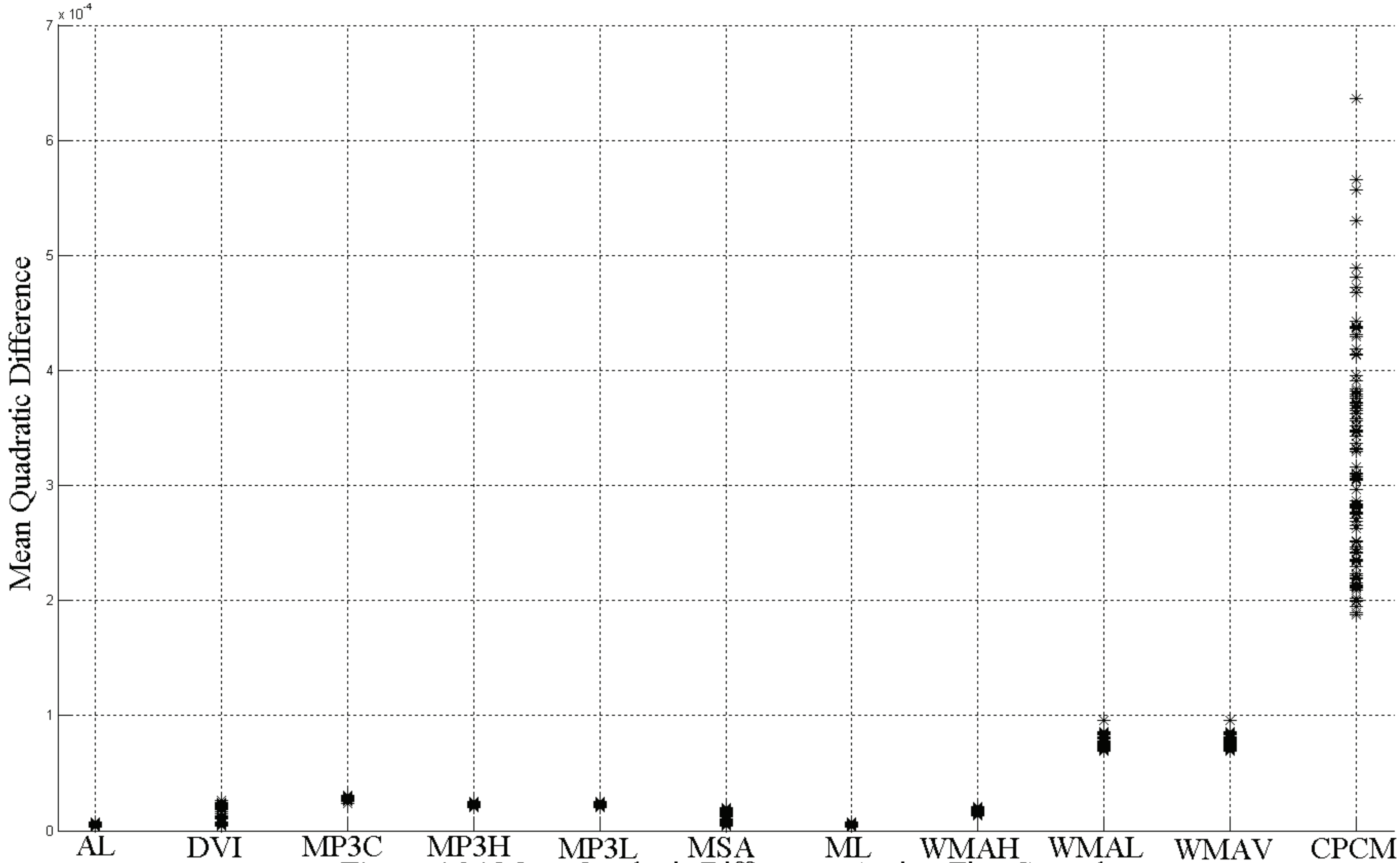

Figure 4.24 Mean Quadratic Differences Against First Control

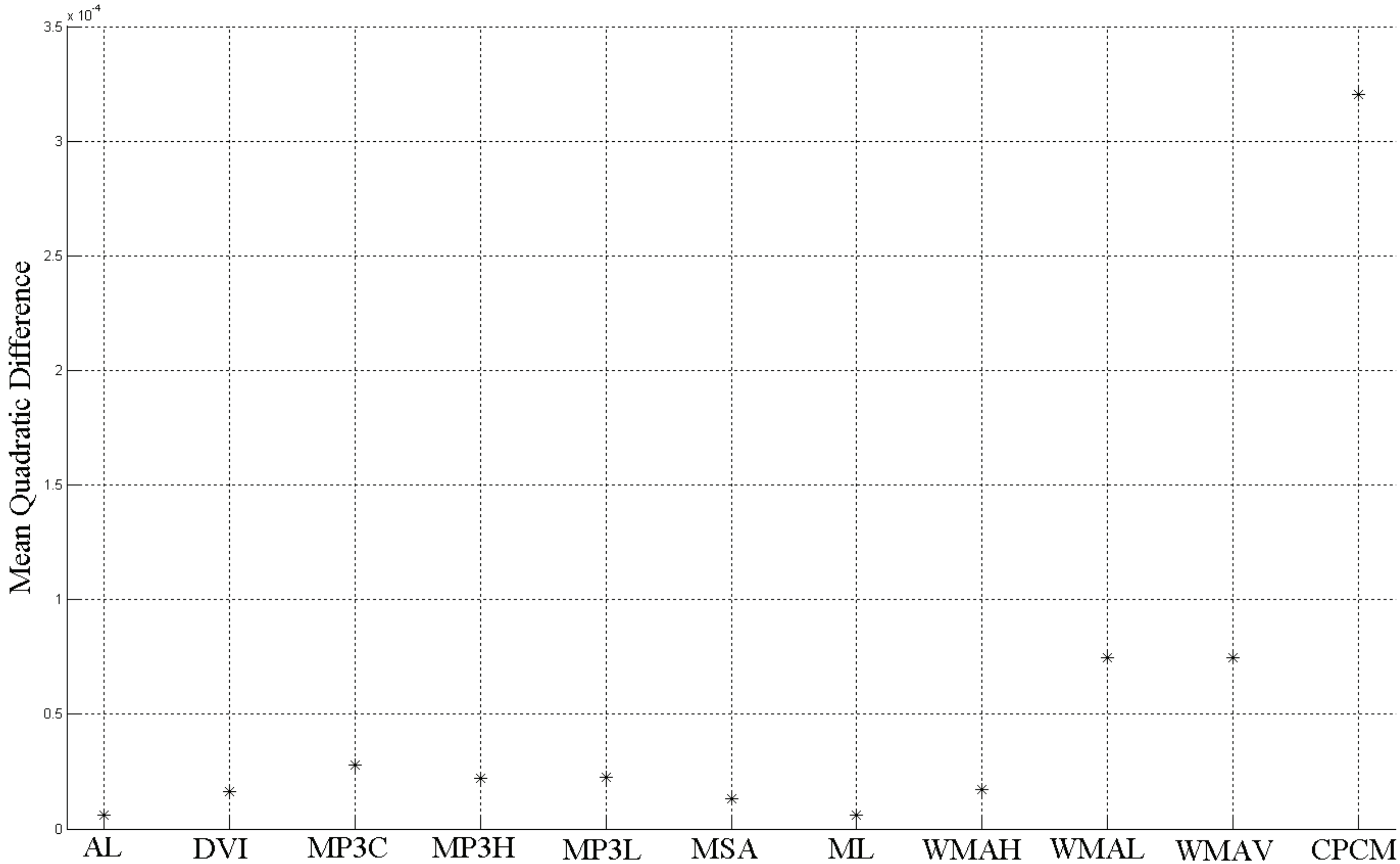

Figure 4.25 Mean Values Of Mean Quadratic Differences Against First Control

Figure 4.26 Standard Deviation Of Mean Quadratic Differences Against First Control

5. Second Control

The second control, to calculate the statistical differences between all the recordings of a compressed format and all the other recordings of that format, returned very low correlation coefficients and high mean quadratic differences. This shows that any two recordings of a compressed format will not create high correlation coefficients or low mean quadratic differences.

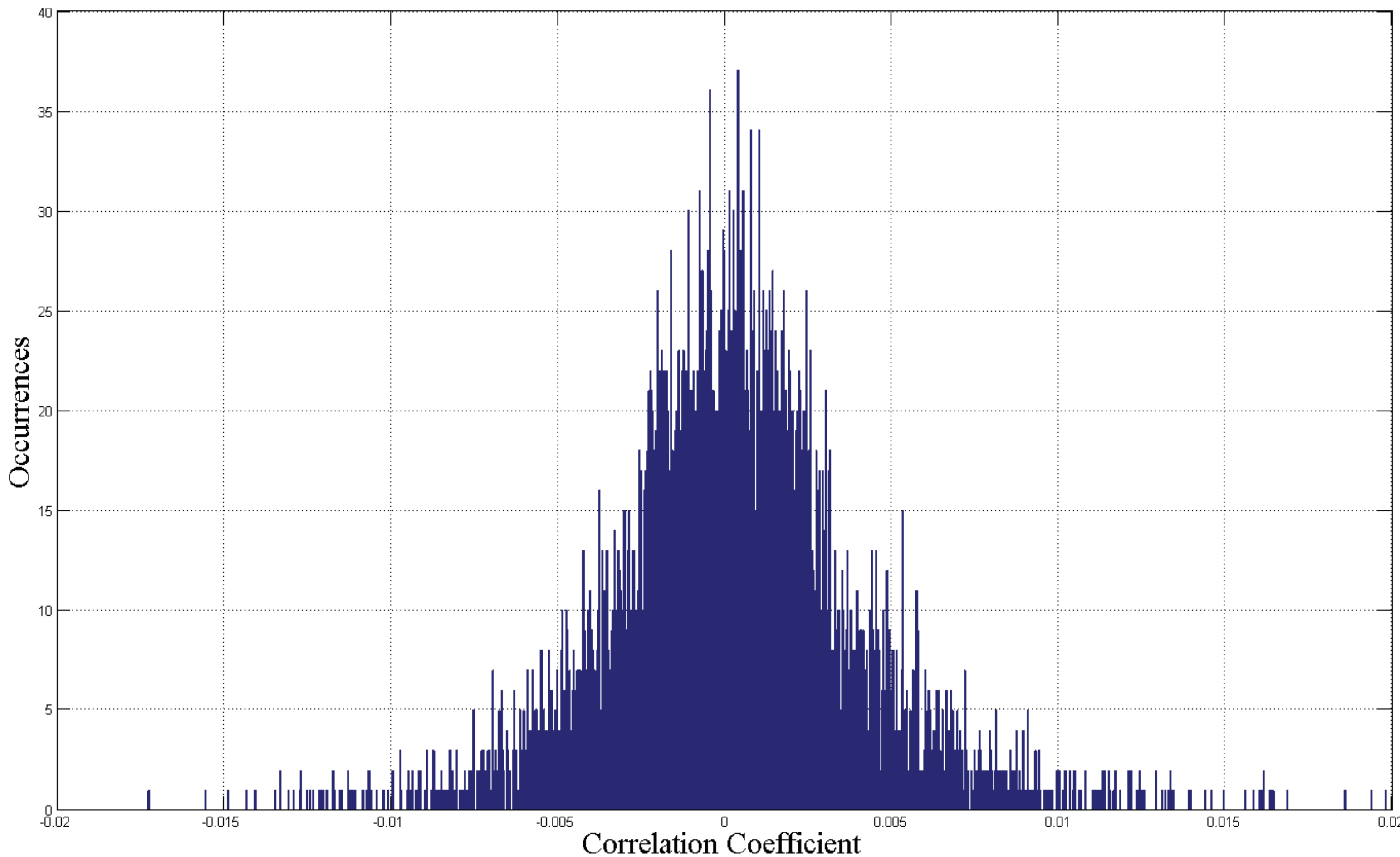

Figure 5.1 Correlation Coefficients With Mean Subtraction Between All A-Law Recordings

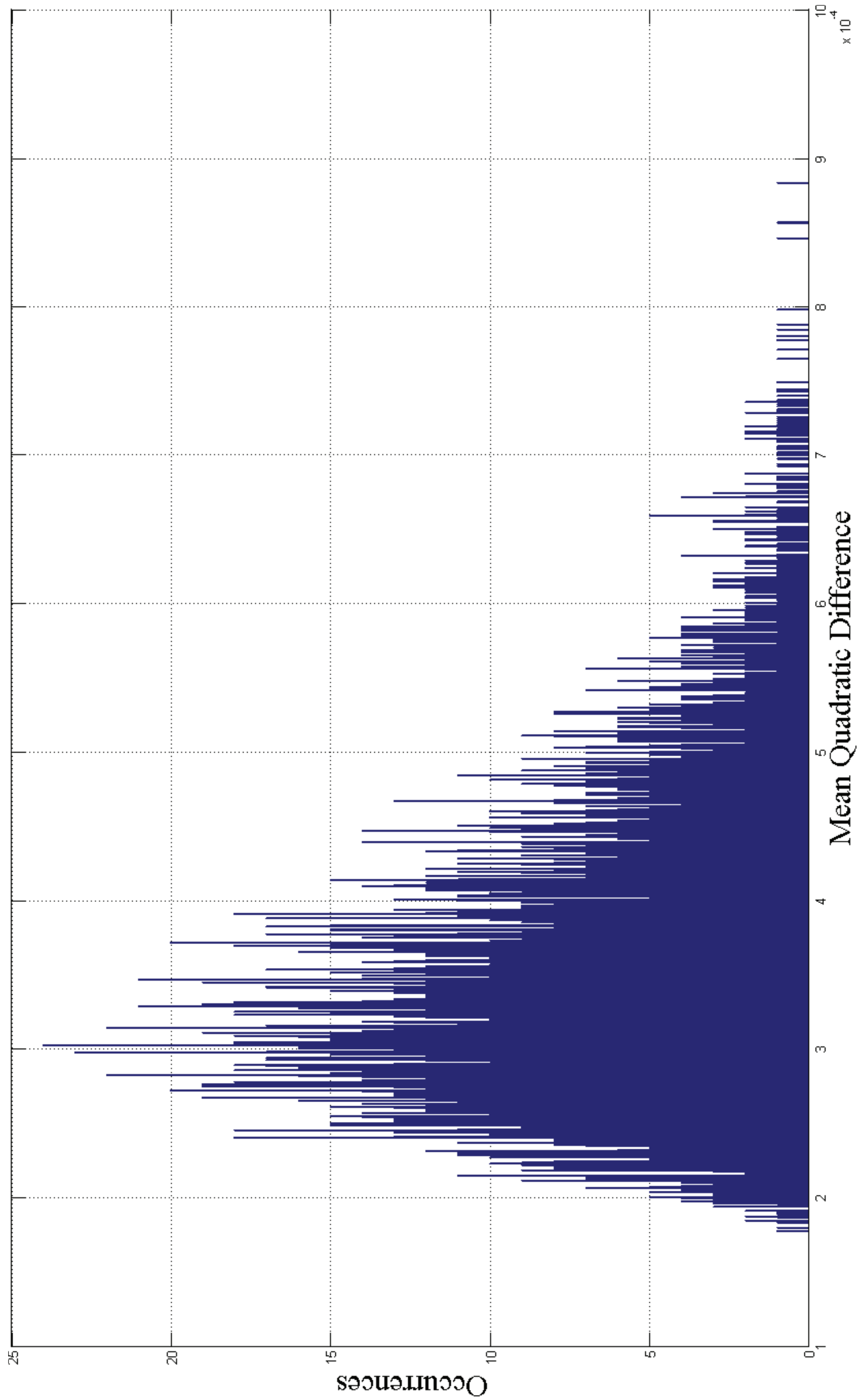

Figure 5.2 Mean Quadratic Differences Between All A-Law Recordings

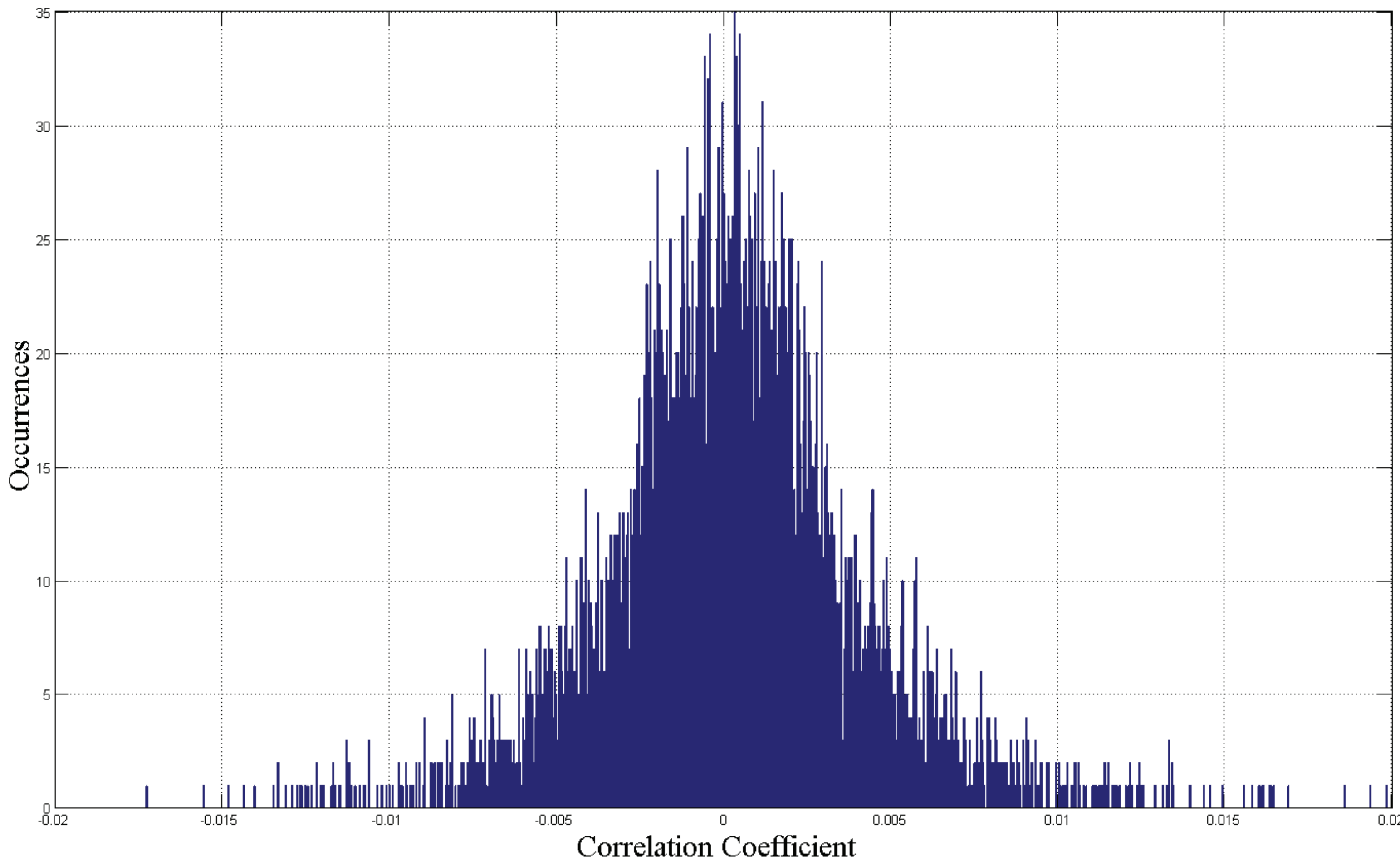

Figure 5.3 Correlation Coefficients With Mean Subtraction Between All DVI ADPCM Recordings

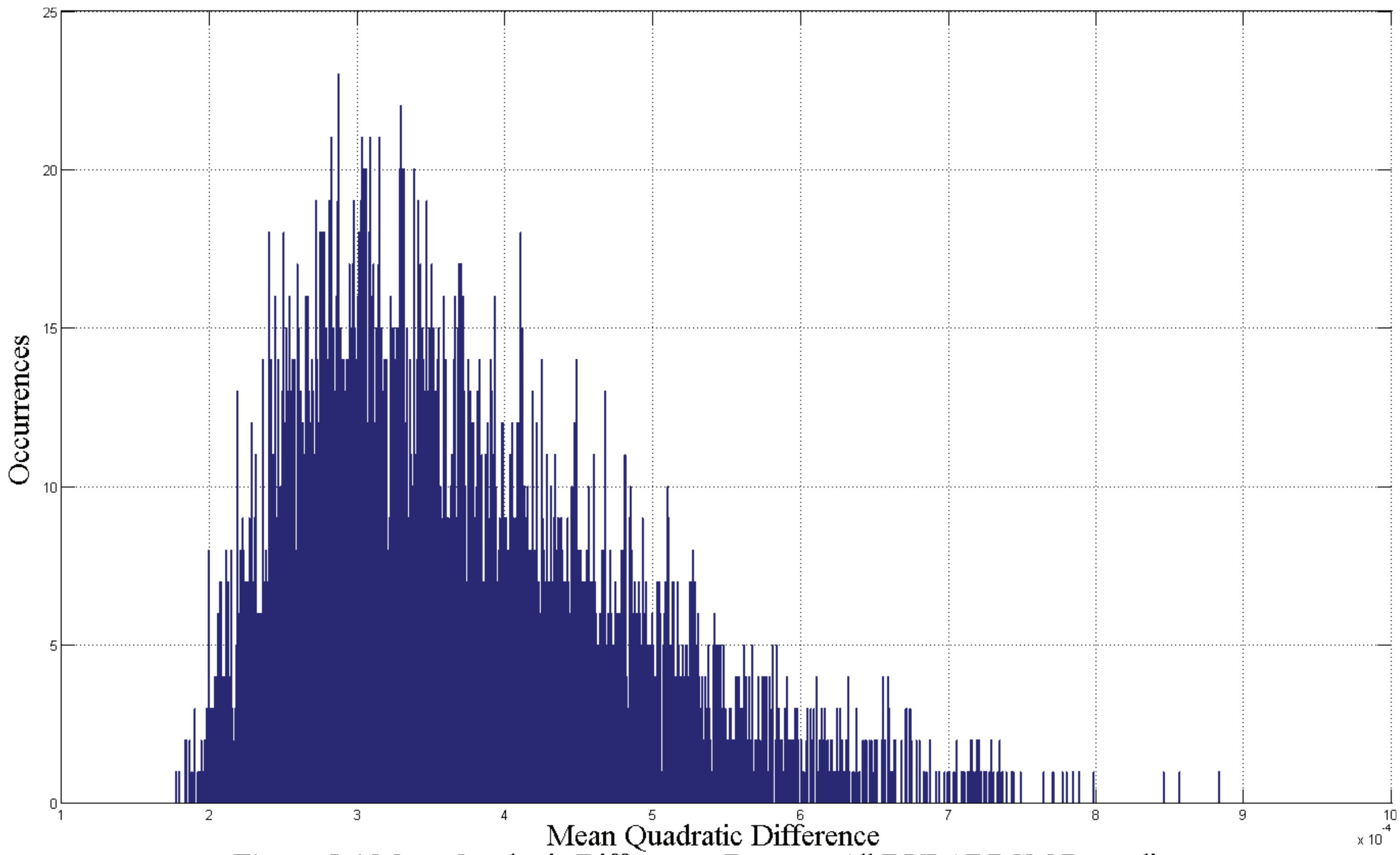

Figure 5.4 Mean Quadratic Differences Between All DVI ADPCM Recordings

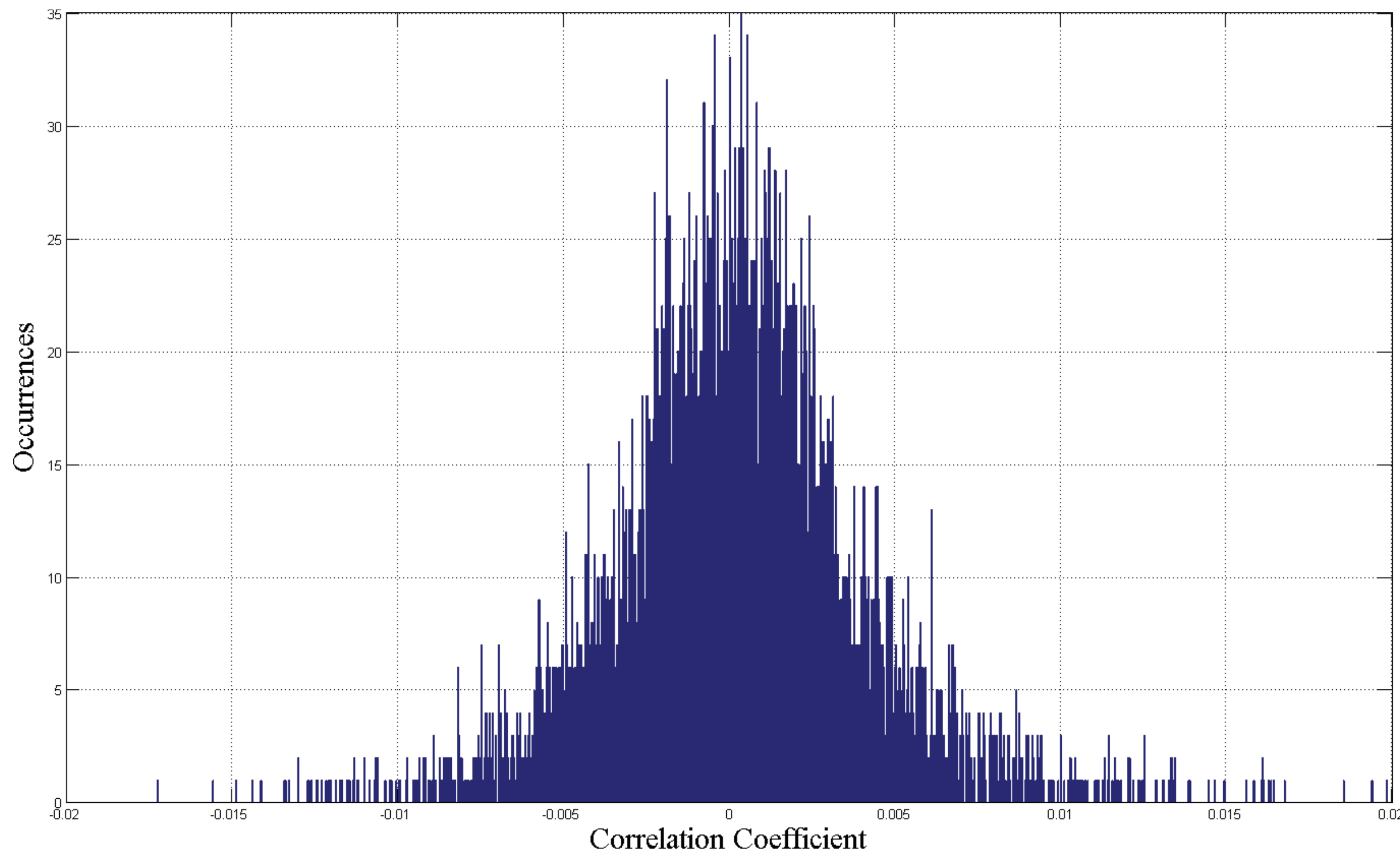

Figure 5.5 Correlation Coefficients With Mean Subtraction Between All MP3 With Constant Bit-Rate Recordings

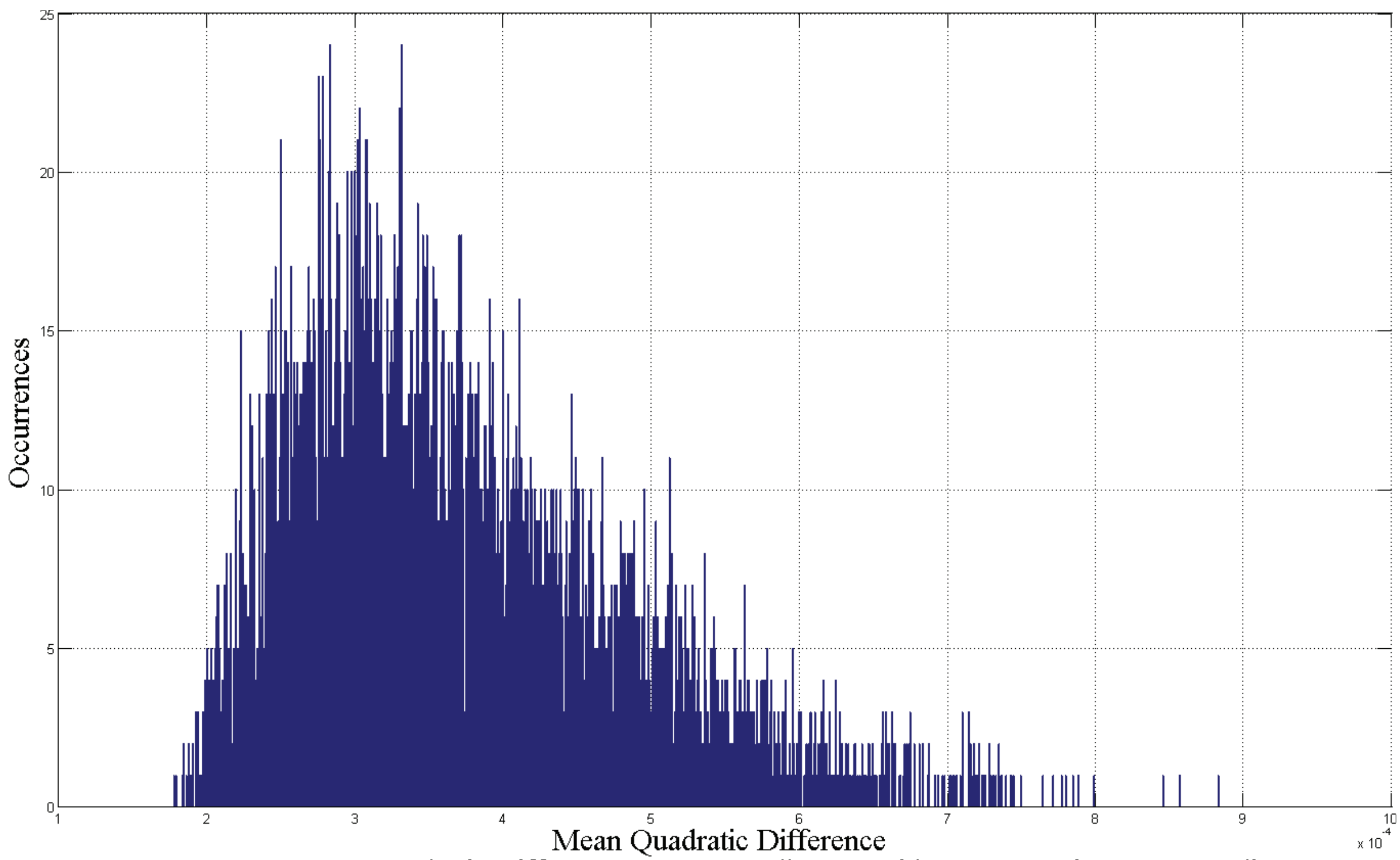

Figure 5.6 Mean Quadratic Differences Between All MP3 With Constant Bit-Rate Recordings

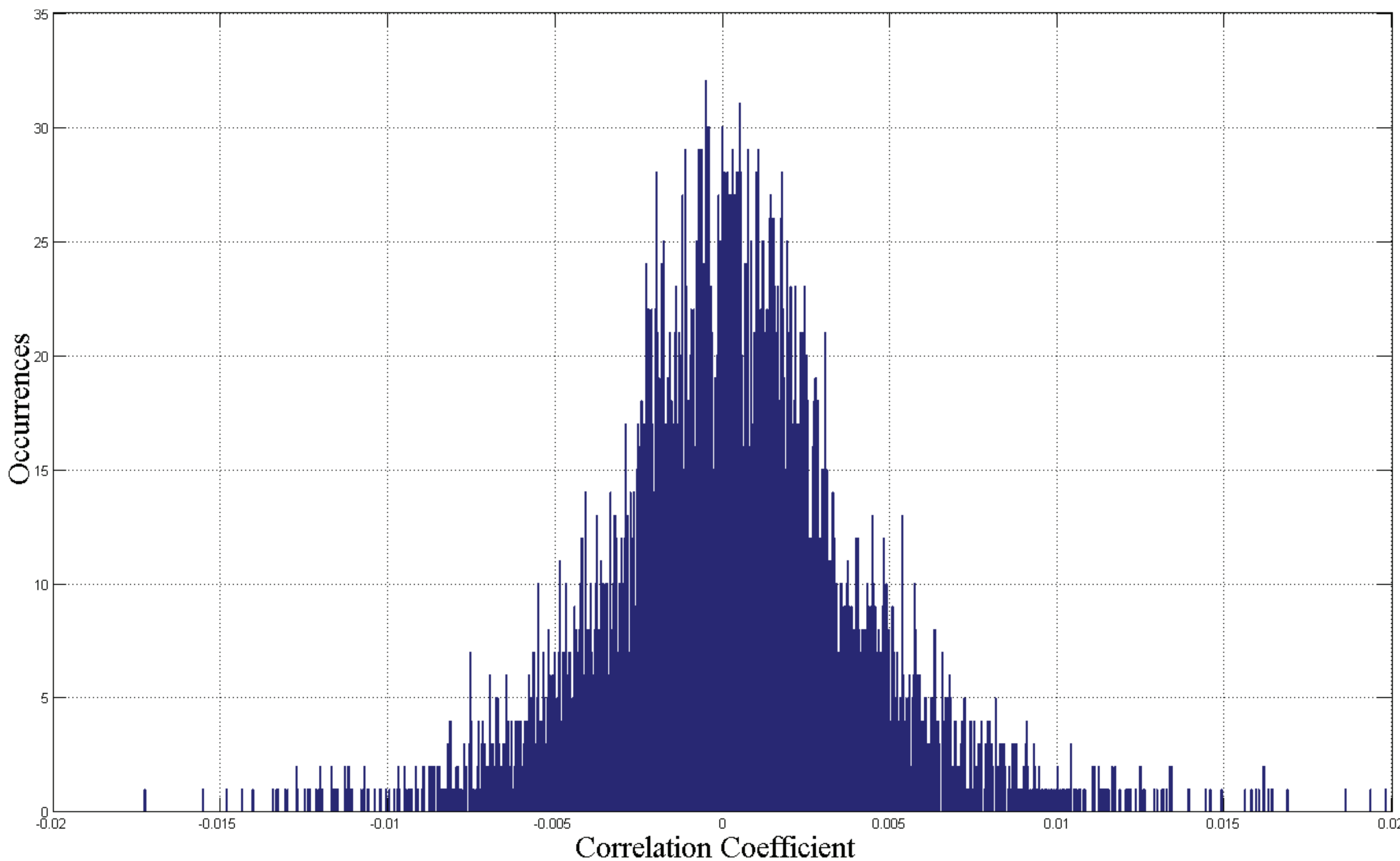

Figure 5.7 Correlation Coefficients With Mean Subtraction Between All High Quality MP3 With Variable Bit-Rate Recordings

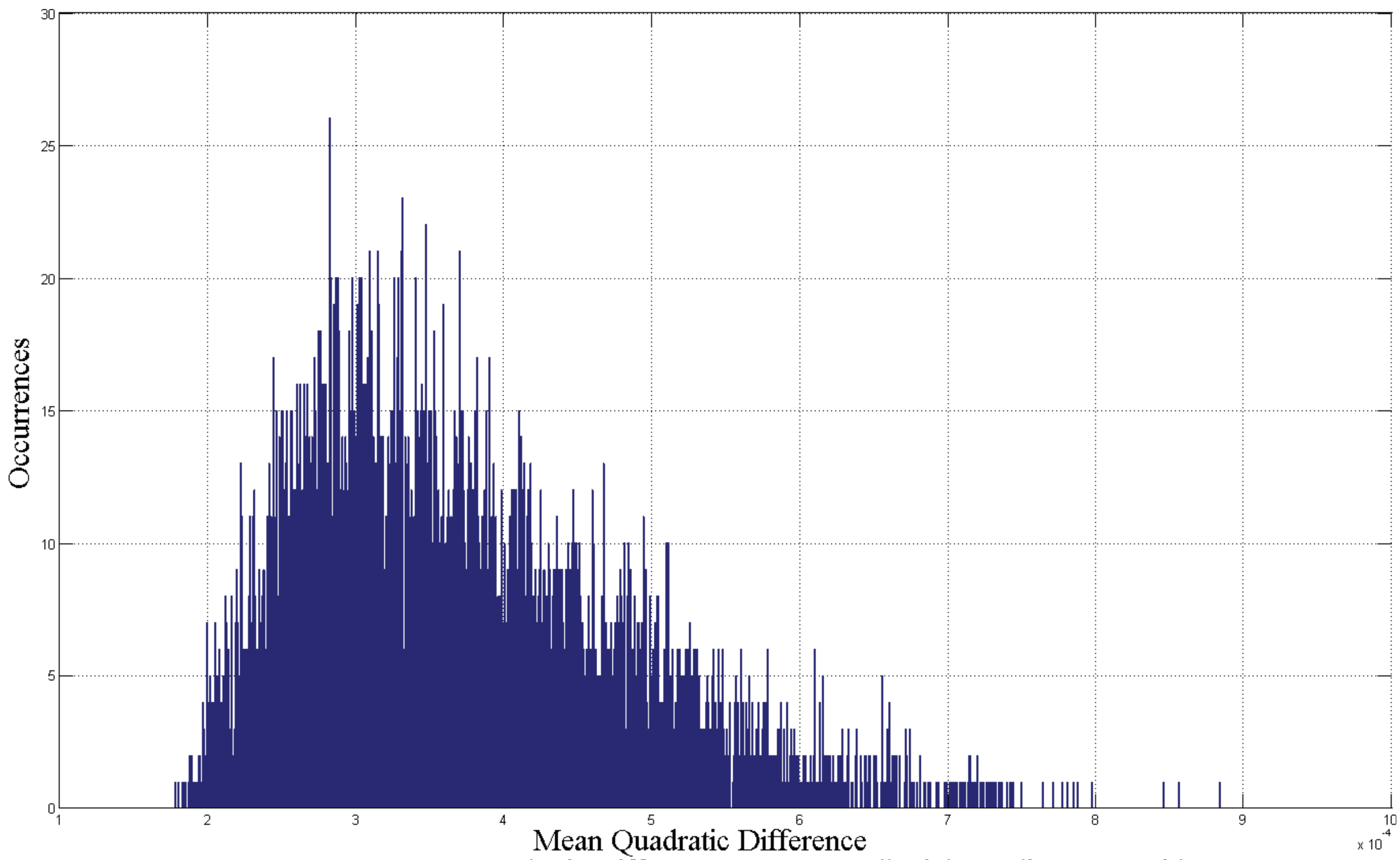

Figure 5.8 Mean Quadratic Differences Between All High Quality MP3 With Variable Bit-Rate Recordings

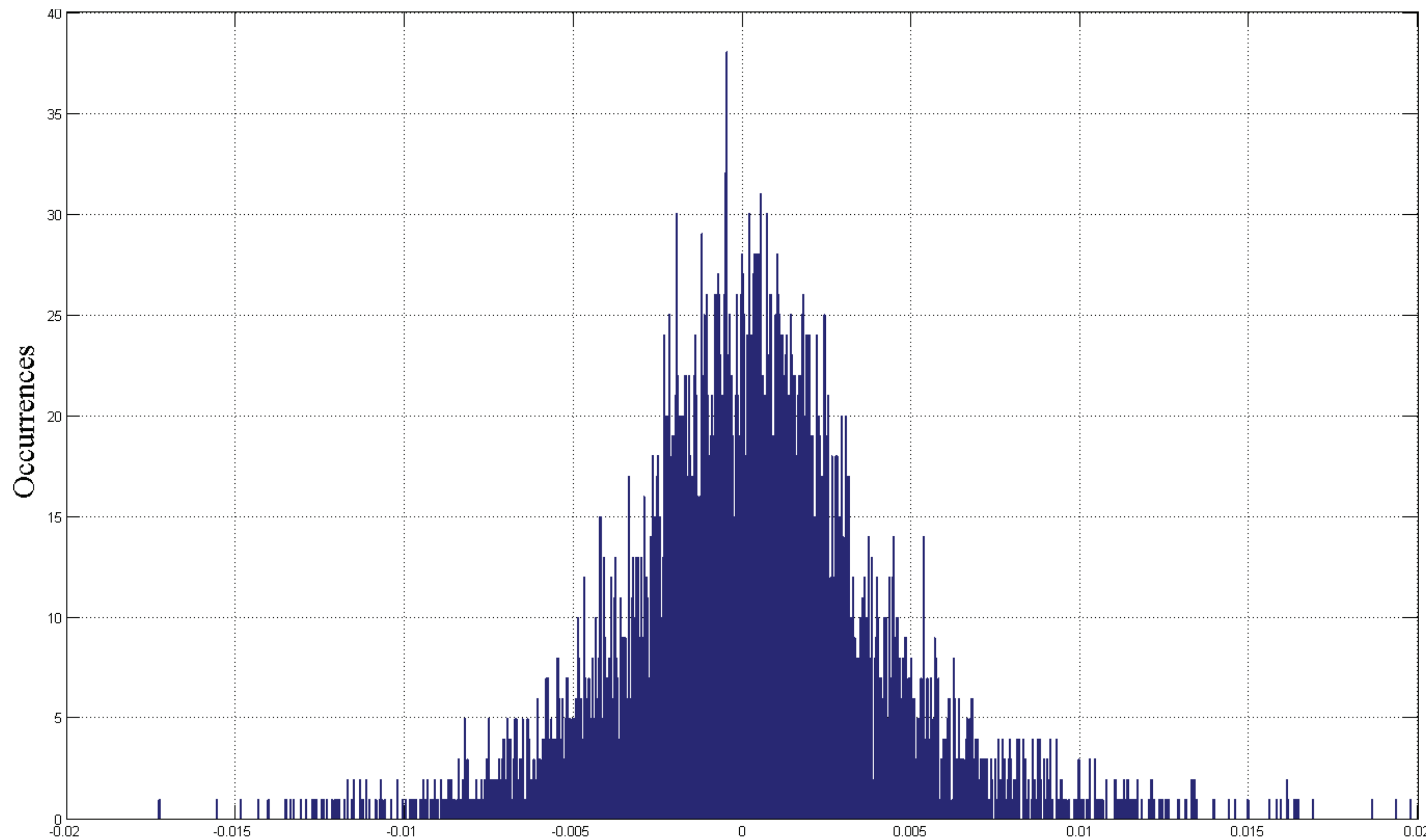

Figure 5.9 Correlation Coefficients With Mean Subtraction Between All Low Quality MP3 With Variable Bit-Rate Recordings

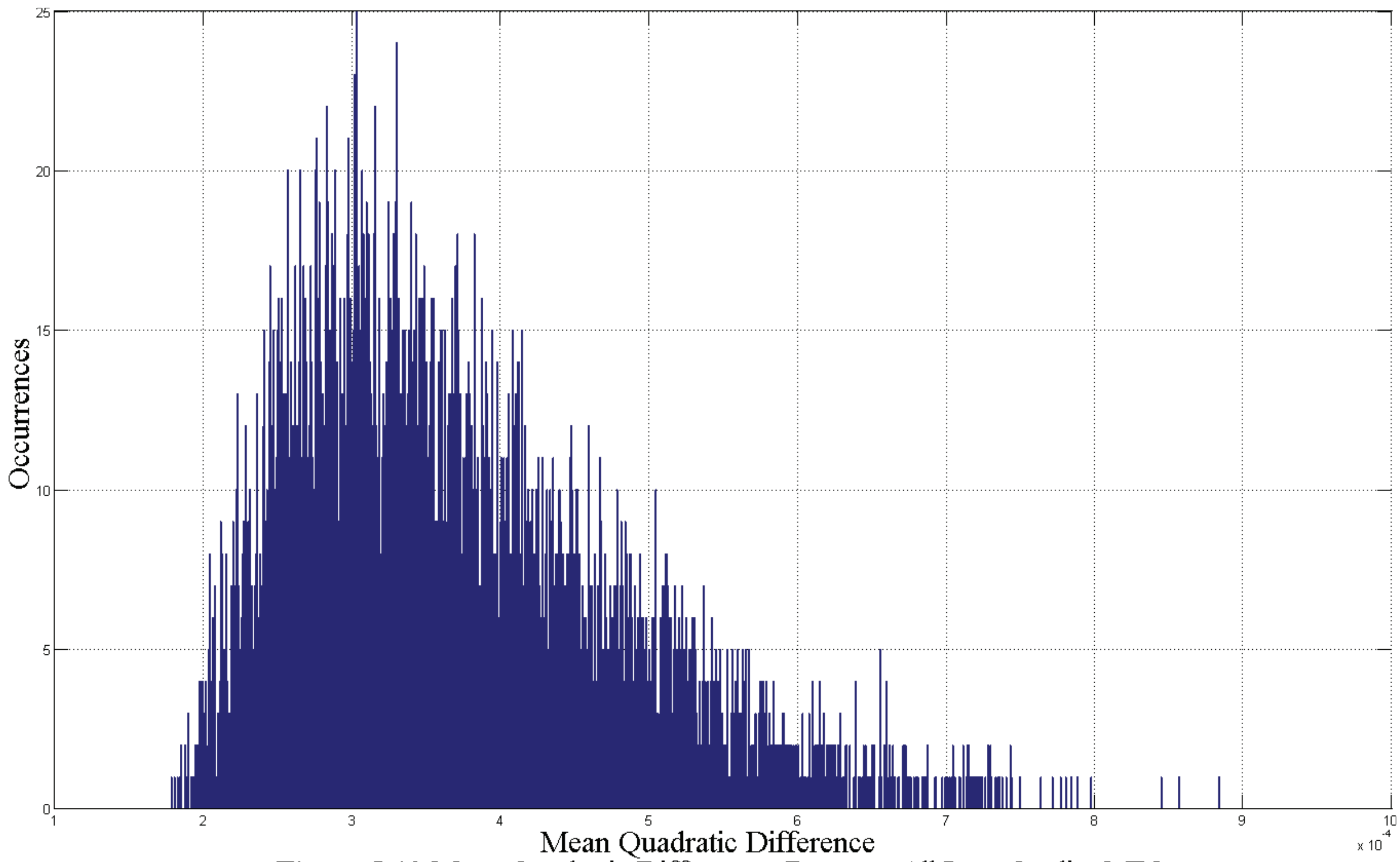

Figure 5.10 Mean Quadratic Differences Between All Low Quality MP3 With Variable Bit-Rate Recordings

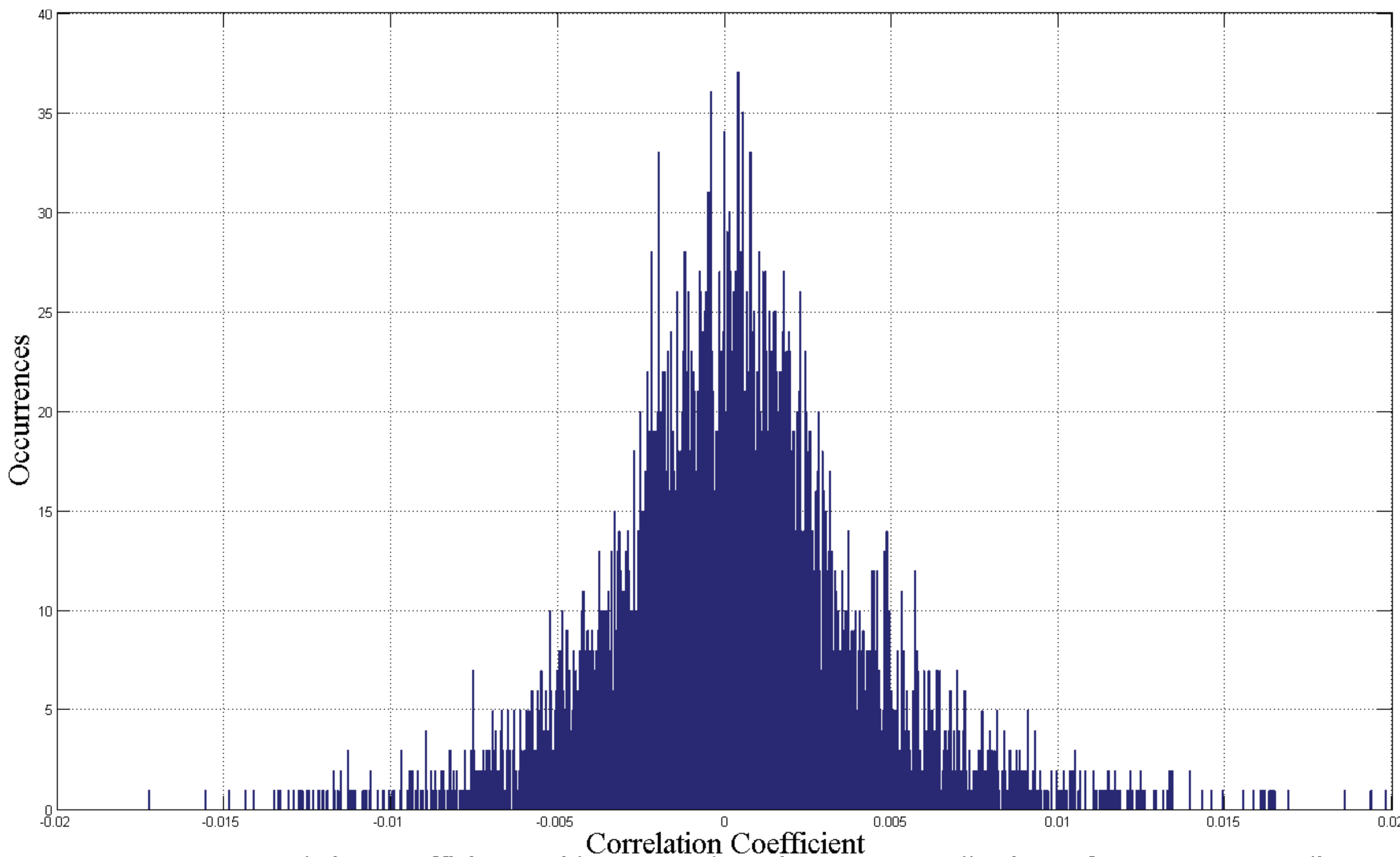

Figure 5.11 Correlation Coefficients With Mean Subtraction Between All Microsoft ADPCM Recordings

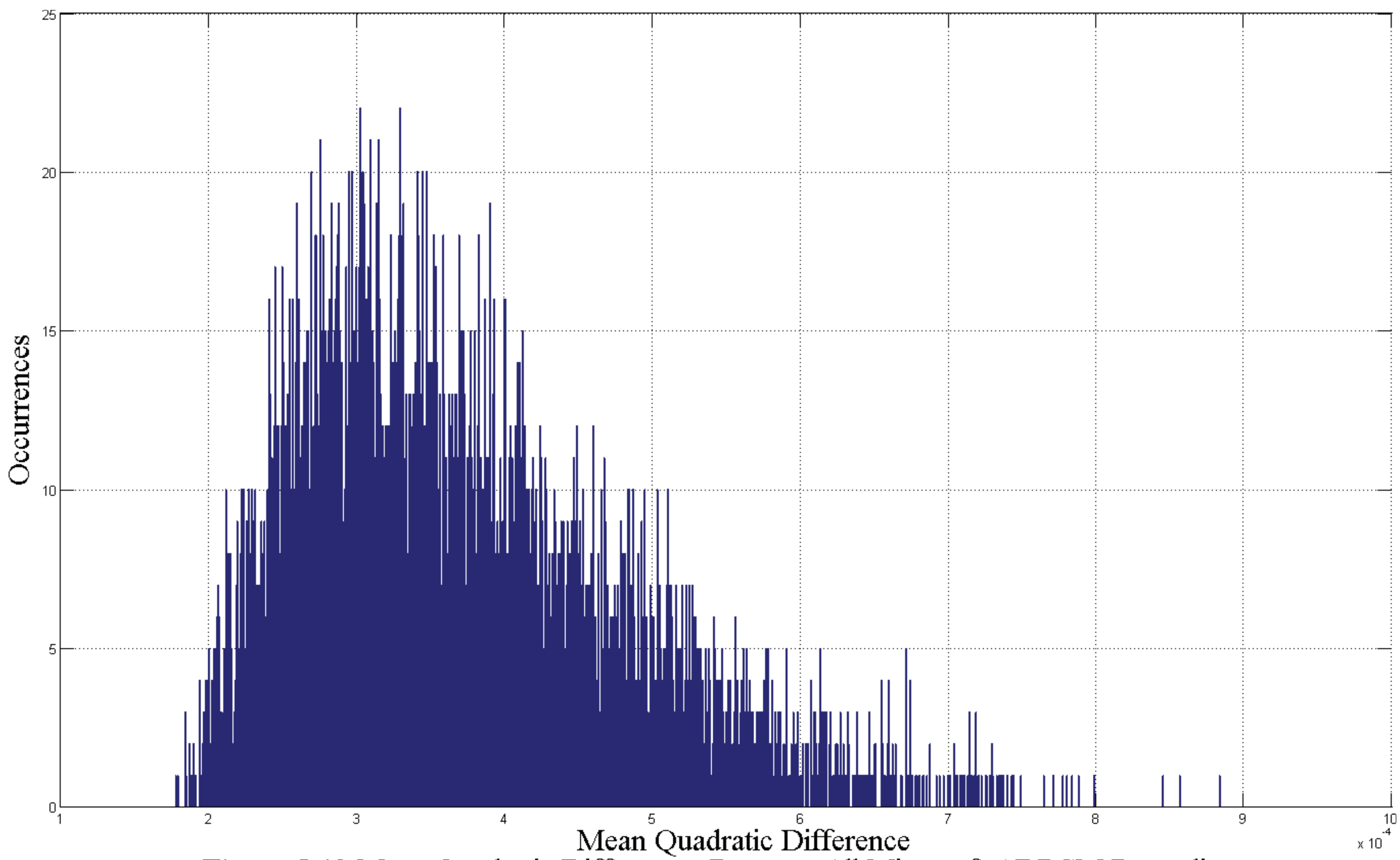

Figure 5.12 Mean Quadratic Differences Between All Microsoft ADPCM Recordings

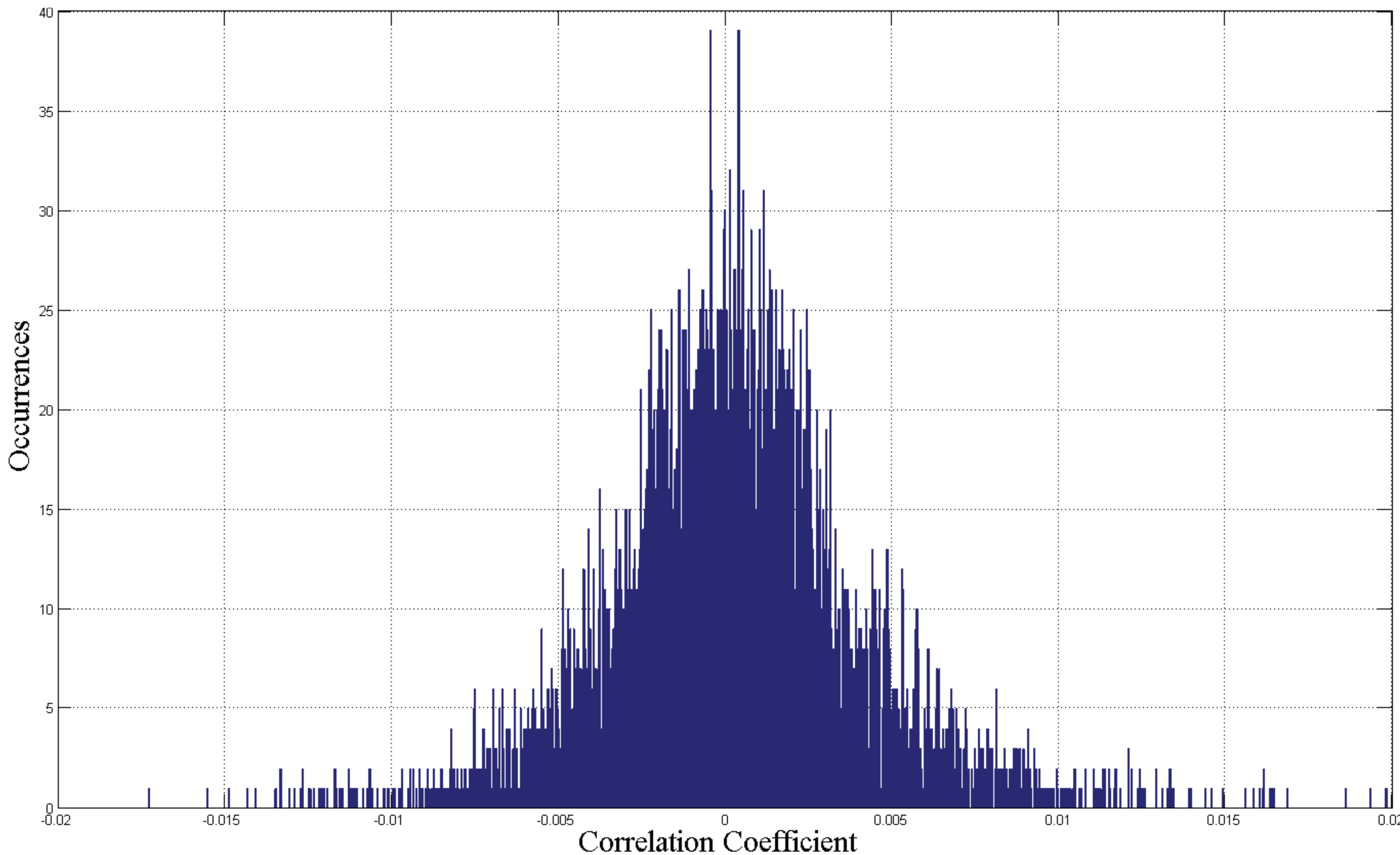

Figure 5.13 Correlation Coefficients With Mean Subtraction Between All Mu-Law Recordings

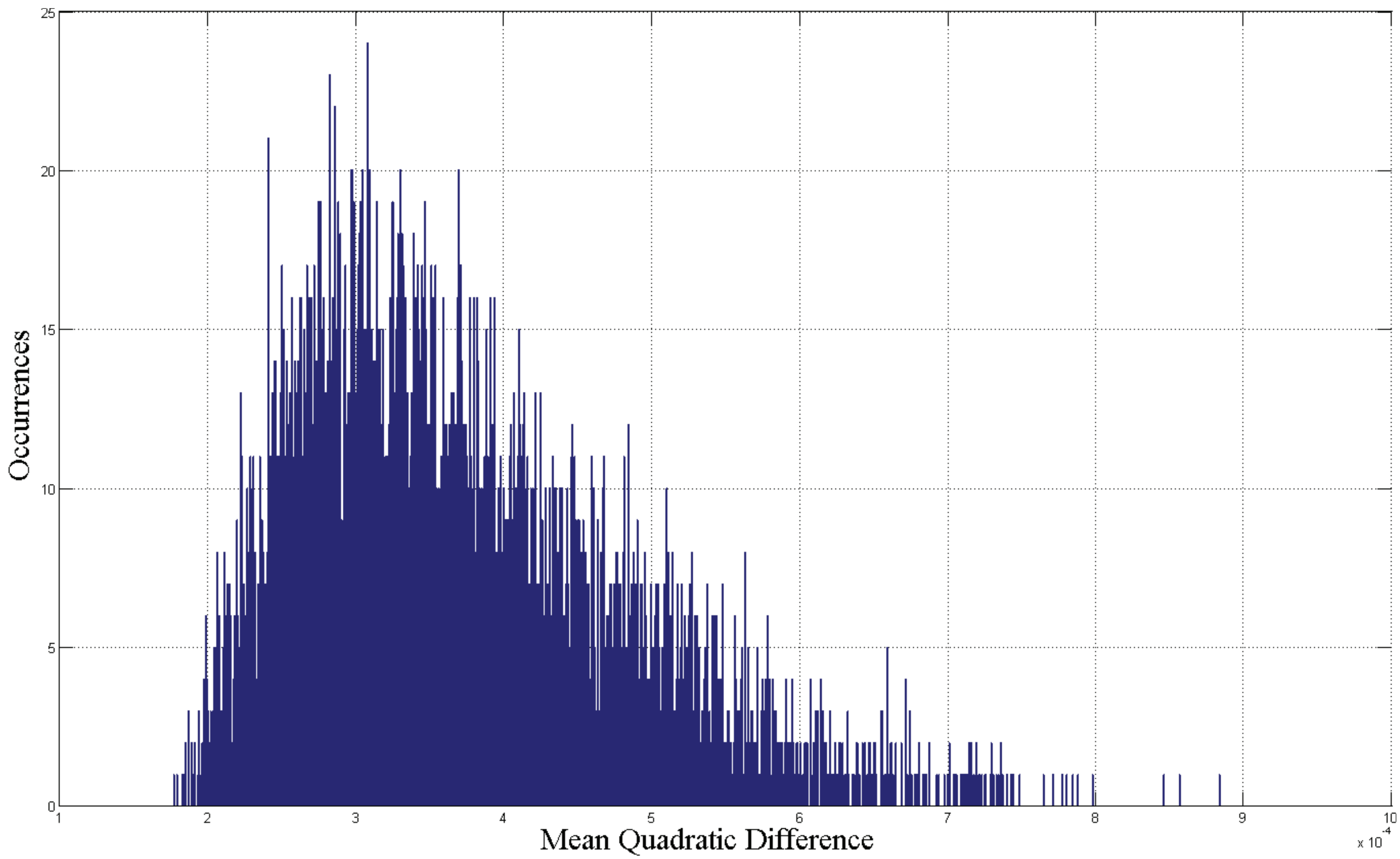

Figure 5.14 Mean Quadratic Differences Between All Mu-Law Recordings

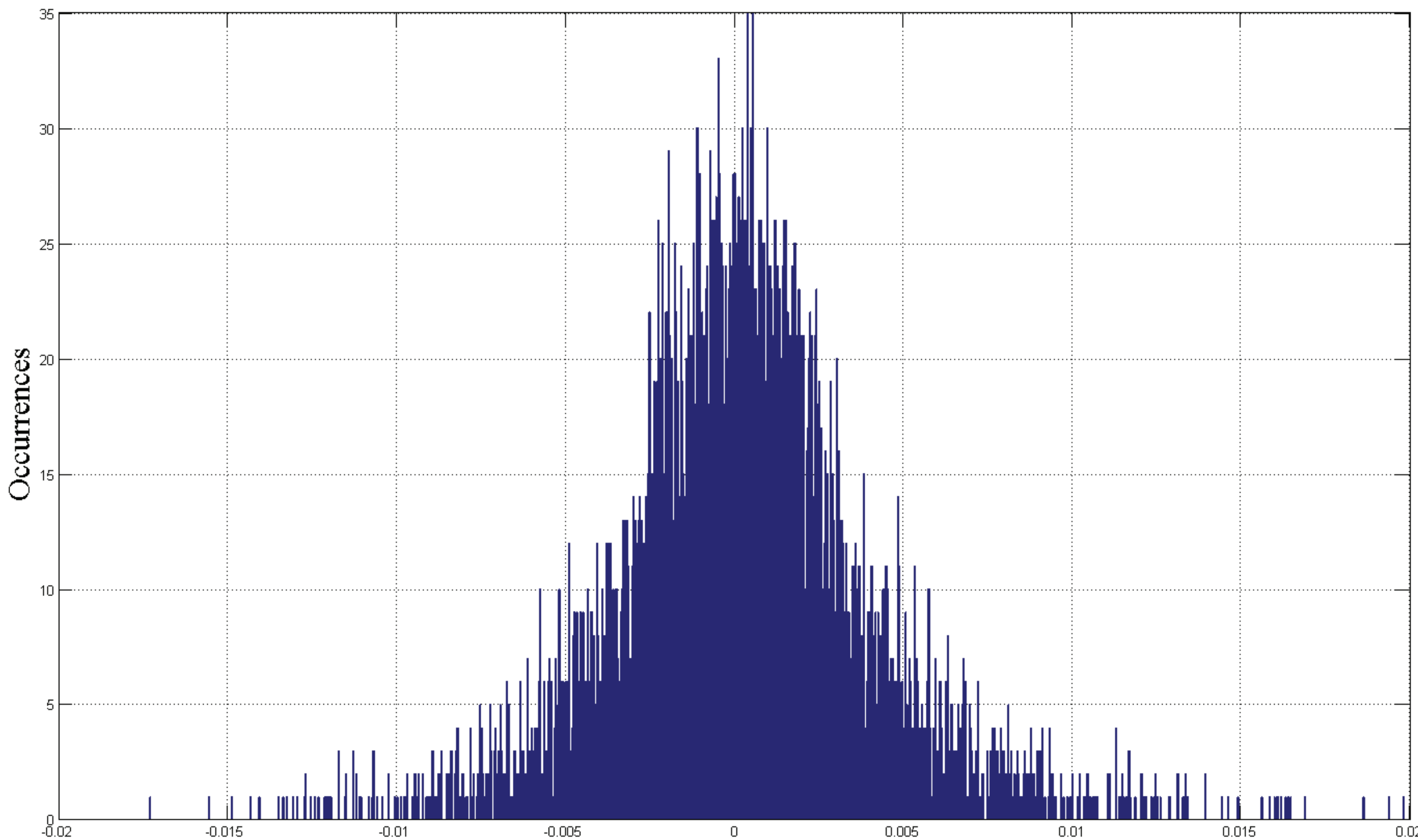

Figure 5.15 Correlation Coefficients With Mean Subtraction Between All High Quality WMA With Constant Bit-Rate Recordings

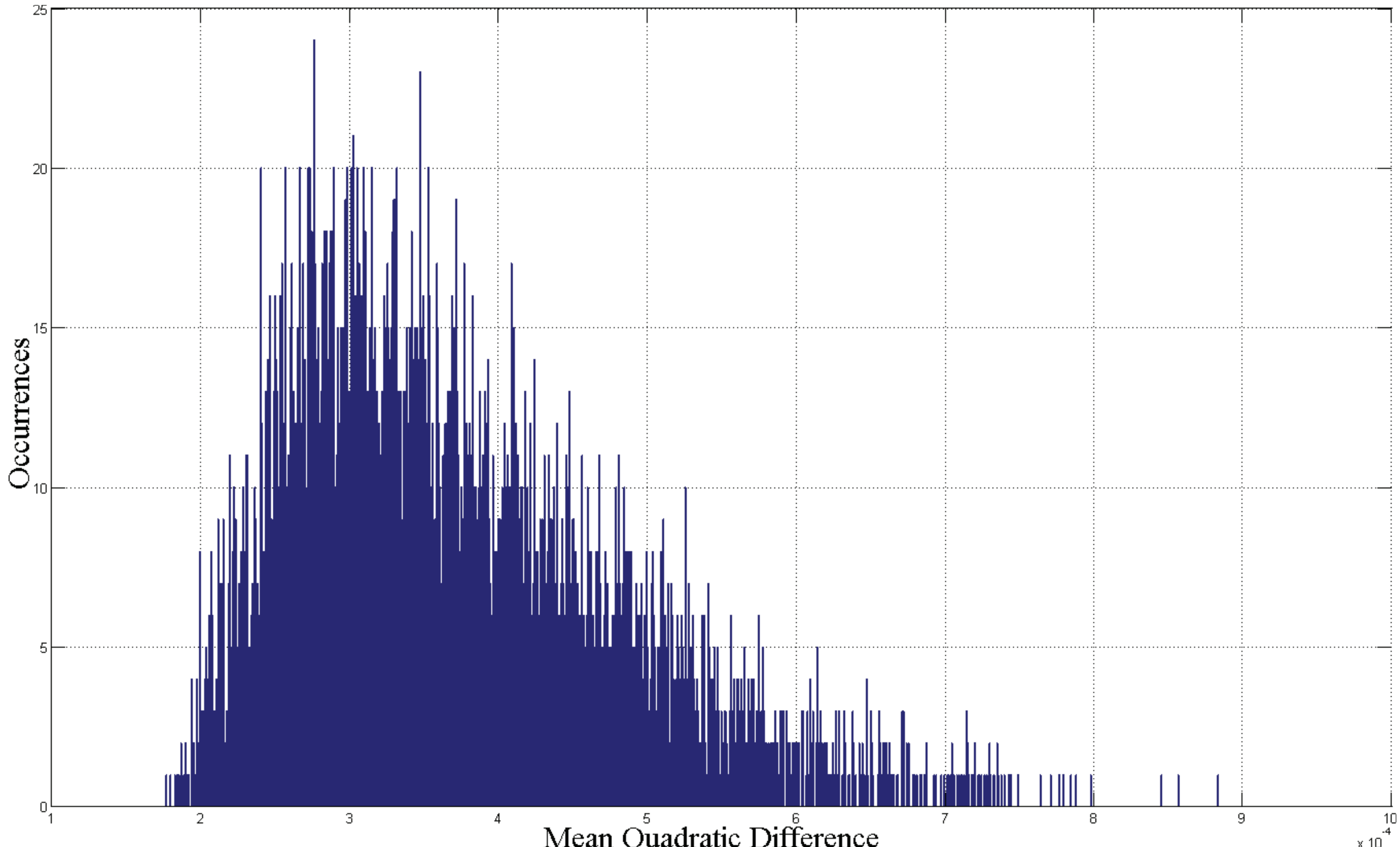

Figure 5.16 Mean Quadratic Differences Between All High Qualtiy WMA With Constant Bit-Rate Recordings

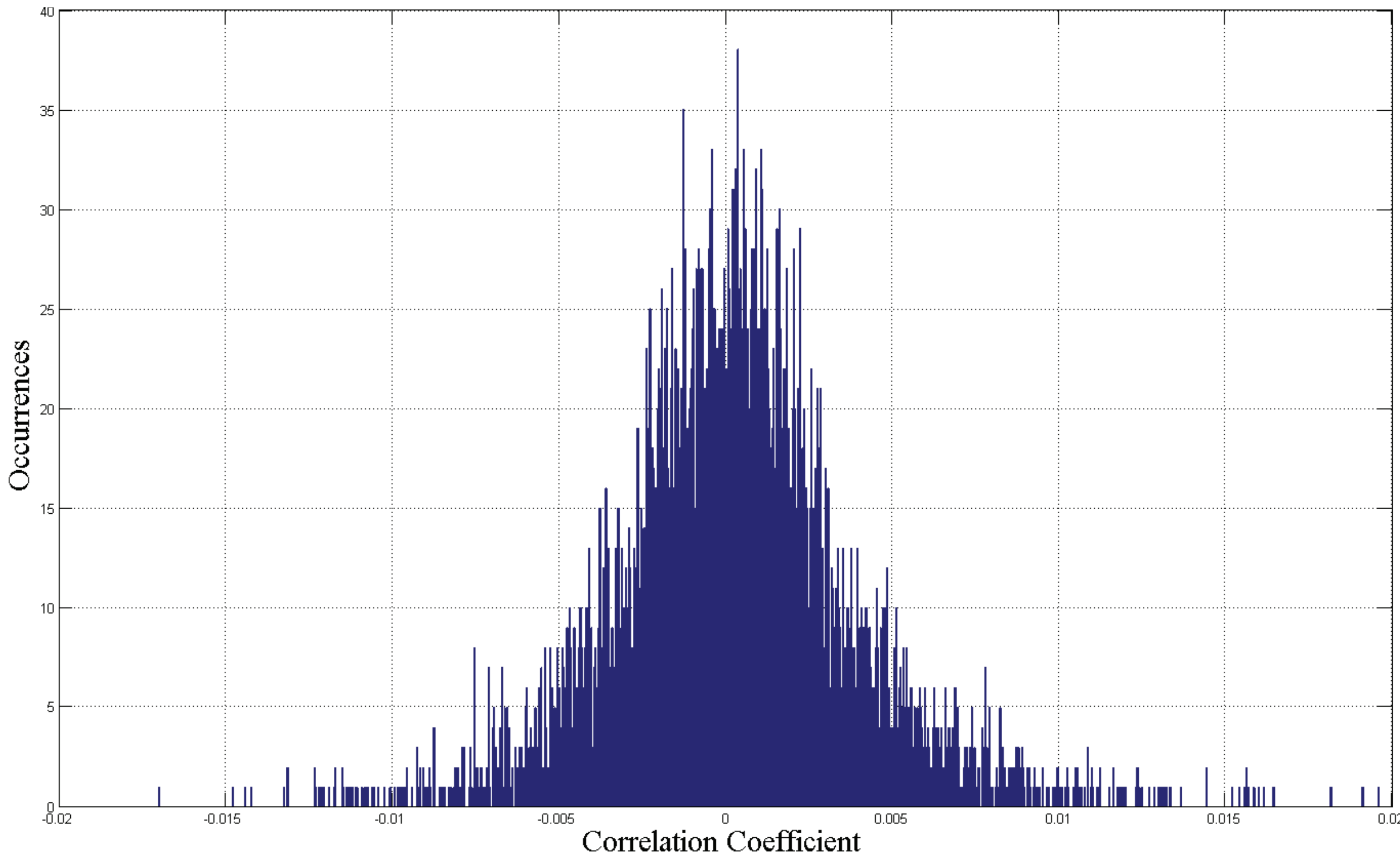

Figure 5.17 Correlation Coefficients With Mean Subtraction Between All Low Quality WMA With Constant Bit-Rate Recordings

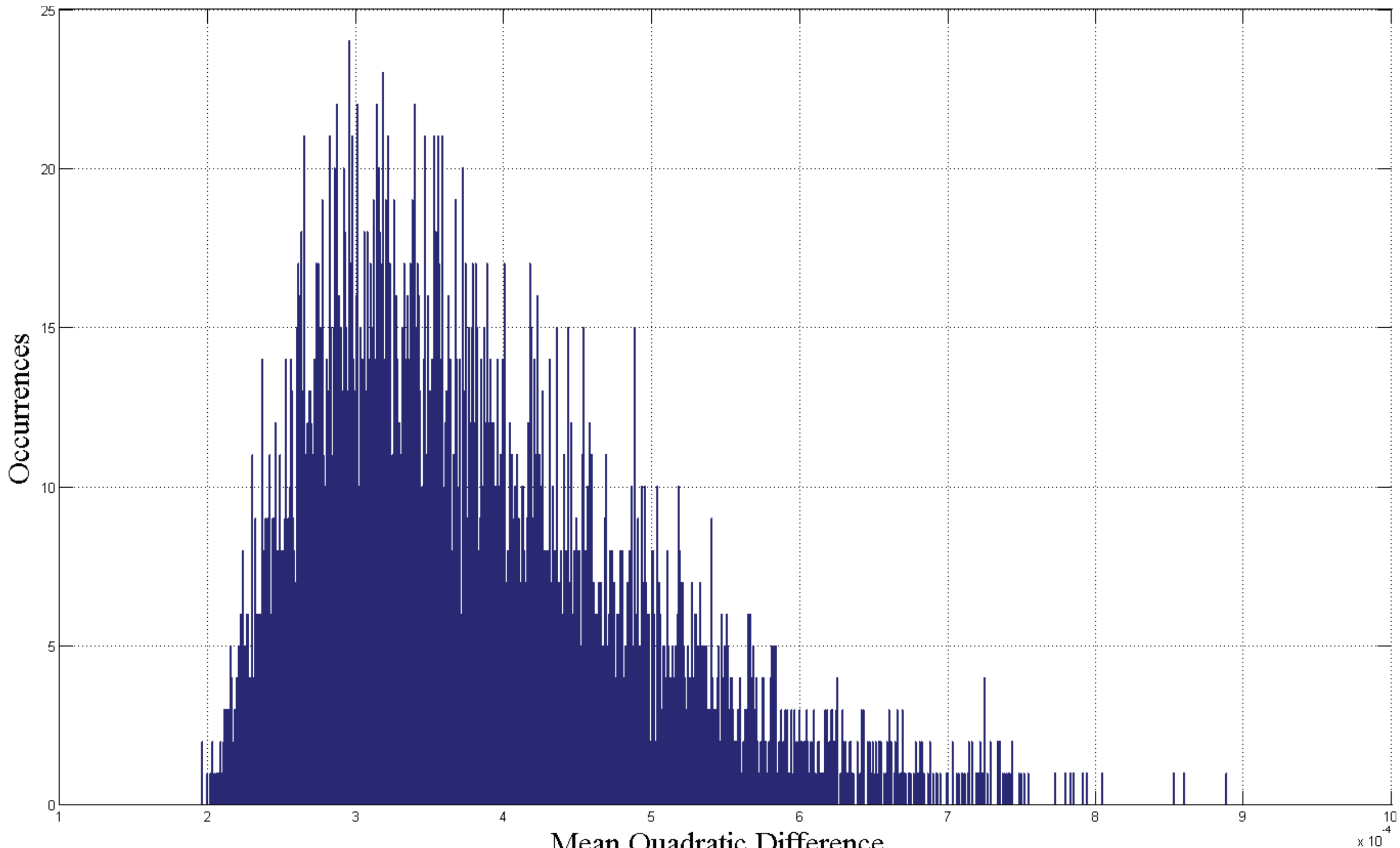

Figure 5.18 Mean Quadratic Differences Between All Low Quality WMA With Constant Bit-Rate Recordings

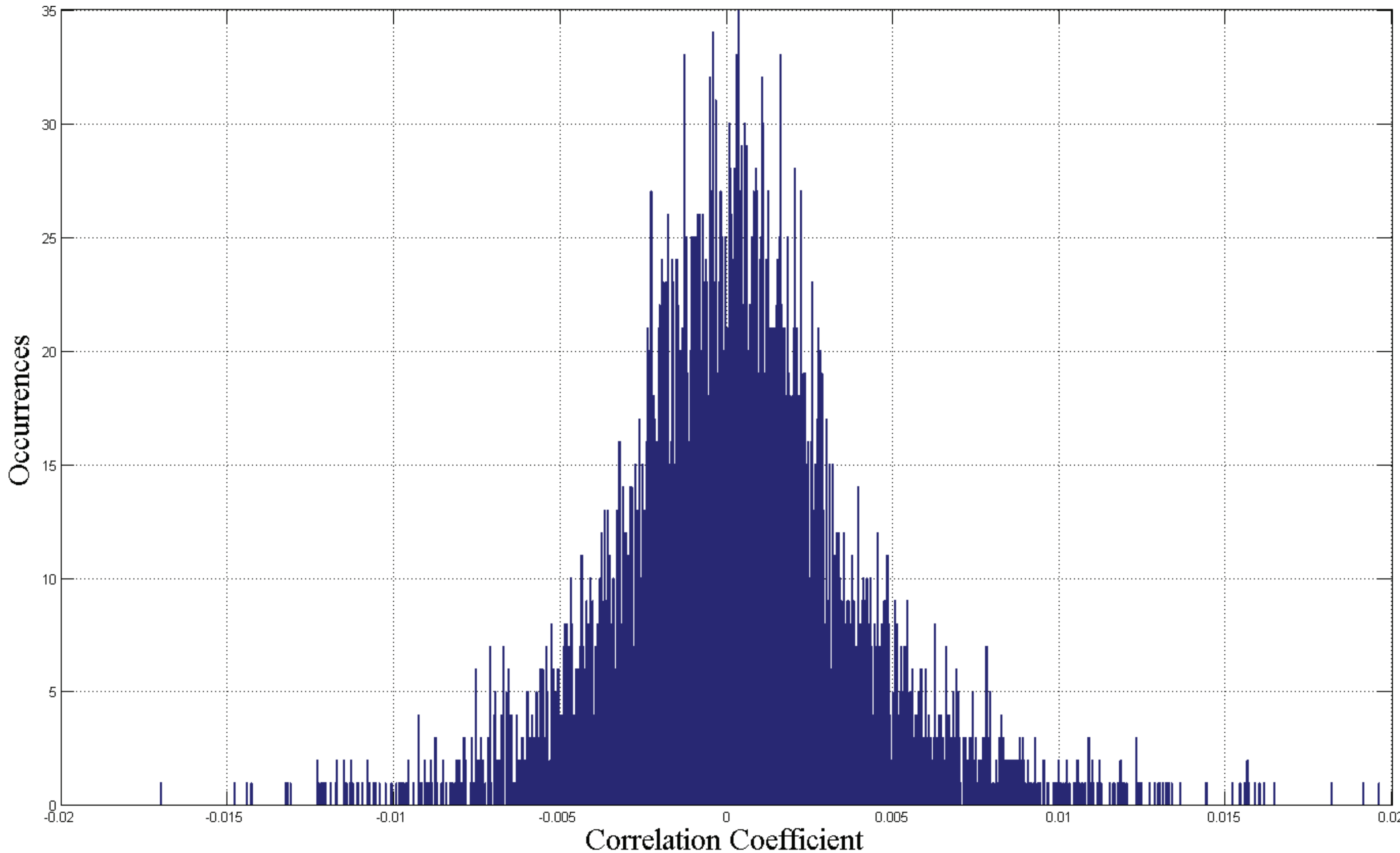

Figure 5.19 Correlation Coefficients With Mean Subtraction Between All WMA With Variable Bit-Rate Recordings

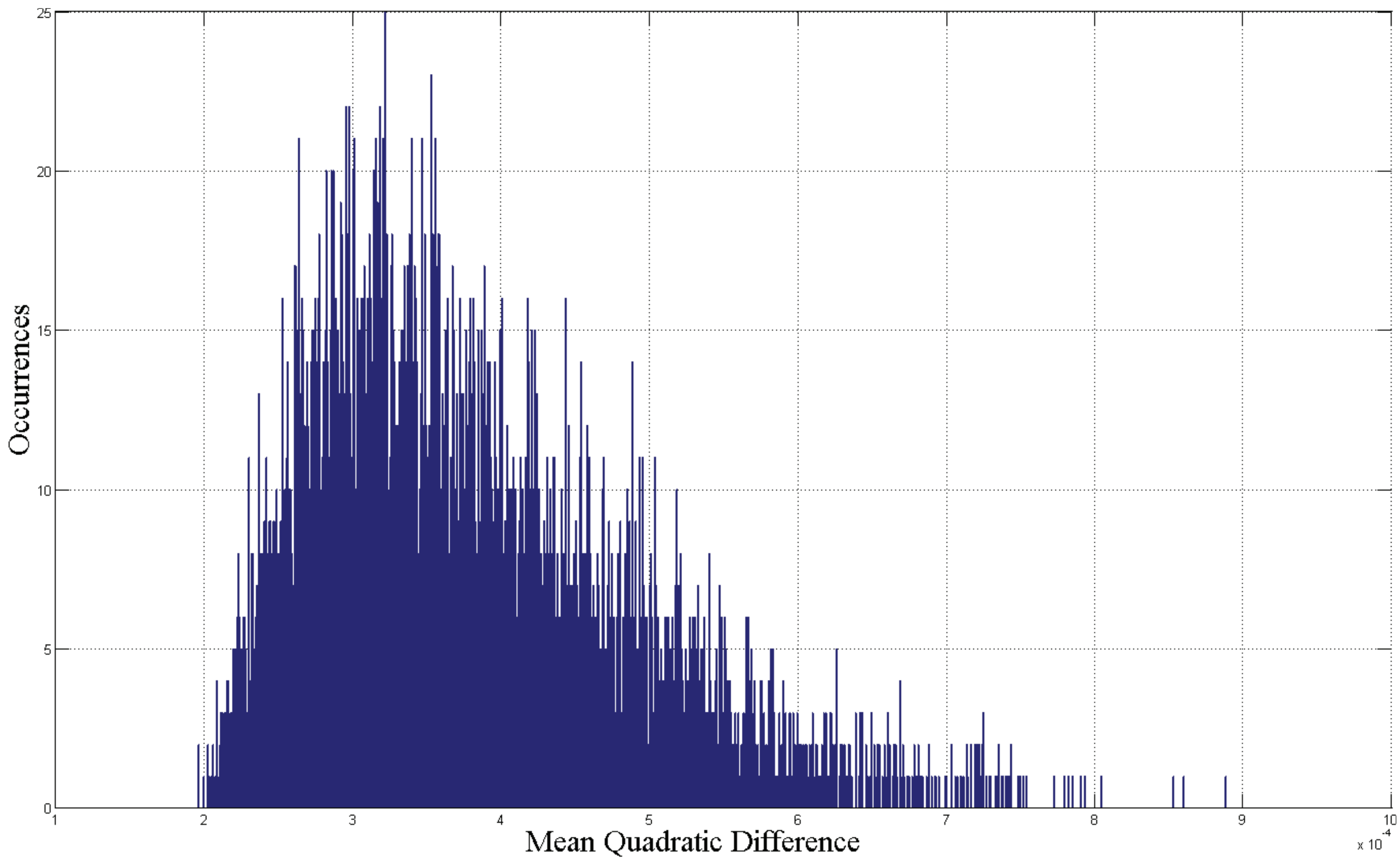

Figure 5.20 Mean Quadratic Differences Between All WMA With Constant Bit-Rate Recordings

6. Third Control

The third control was to calculate for each compressed format the statistical differences between every hour's compressed audio file frequency vector and every hour's PCM audio file frequency vector. All compressed audio files of a format were compared to all PCM audio files. It returned very low correlation coefficients and very high mean quadratic differences when a compressed format's vector was not compared with the corresponding PCM hour's vector. When the vectors were compared with the corresponding PCM hour's vector, the results returned were as reported in the preceding sections on correlation coefficients and mean quadratic differences. These results have been plotted in histograms to illustrate the wide gap between correlation coefficients and mean quadratic differences for matching hours and non-matching hours. This shows that an audio file of a compressed format will not produce high correlation coefficients or low mean quadratic differences when compared with another hour's PCM frequency vector. Intravariablity refers to a compressed audio file being compared with the corresponding hour's PCM vector; whereas itervariability refers to a compressed audio file being compared with any audio file that did not come from the same hour.

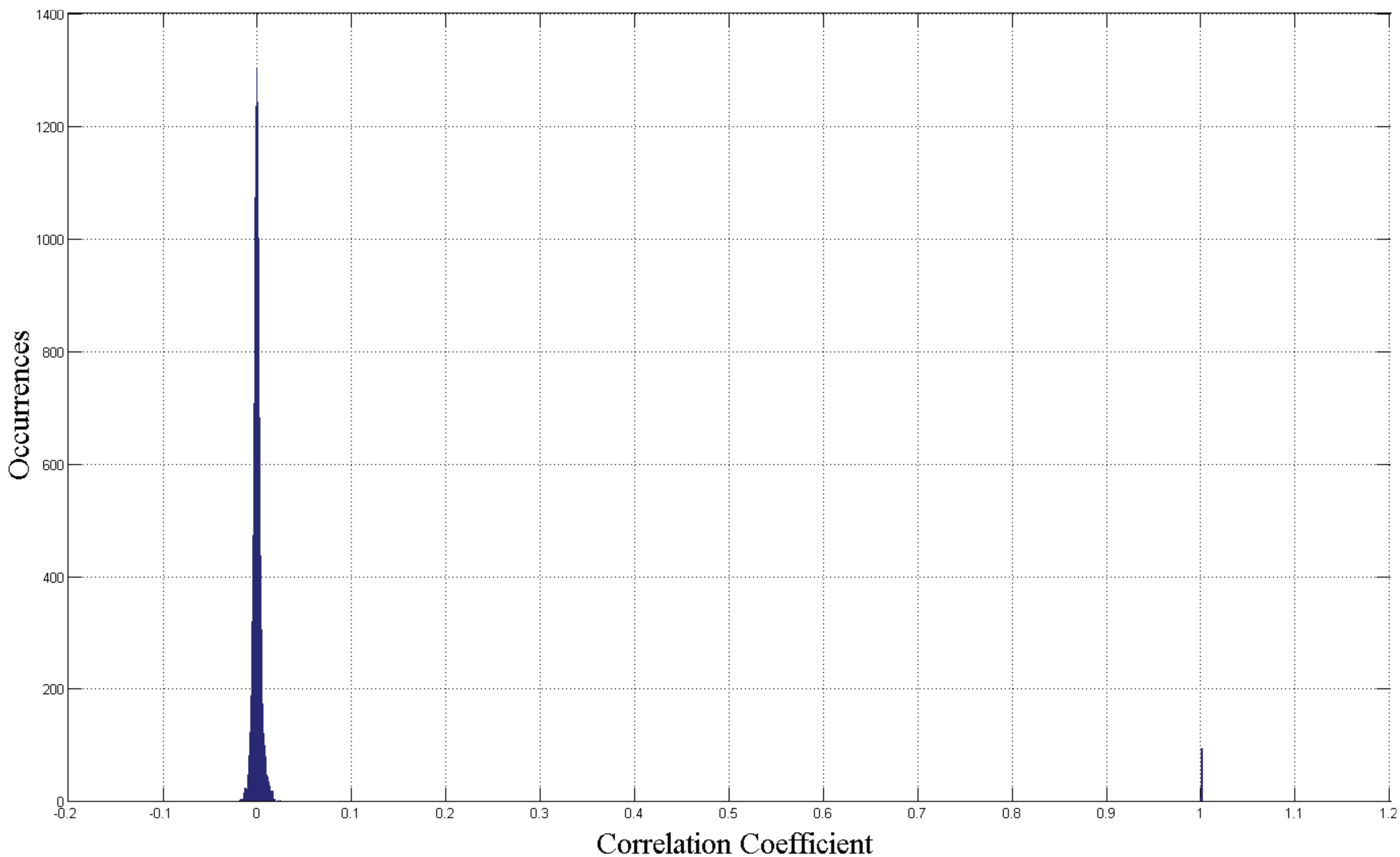

Figure 6.1 A-Law CC Intravariability V. Intervariability

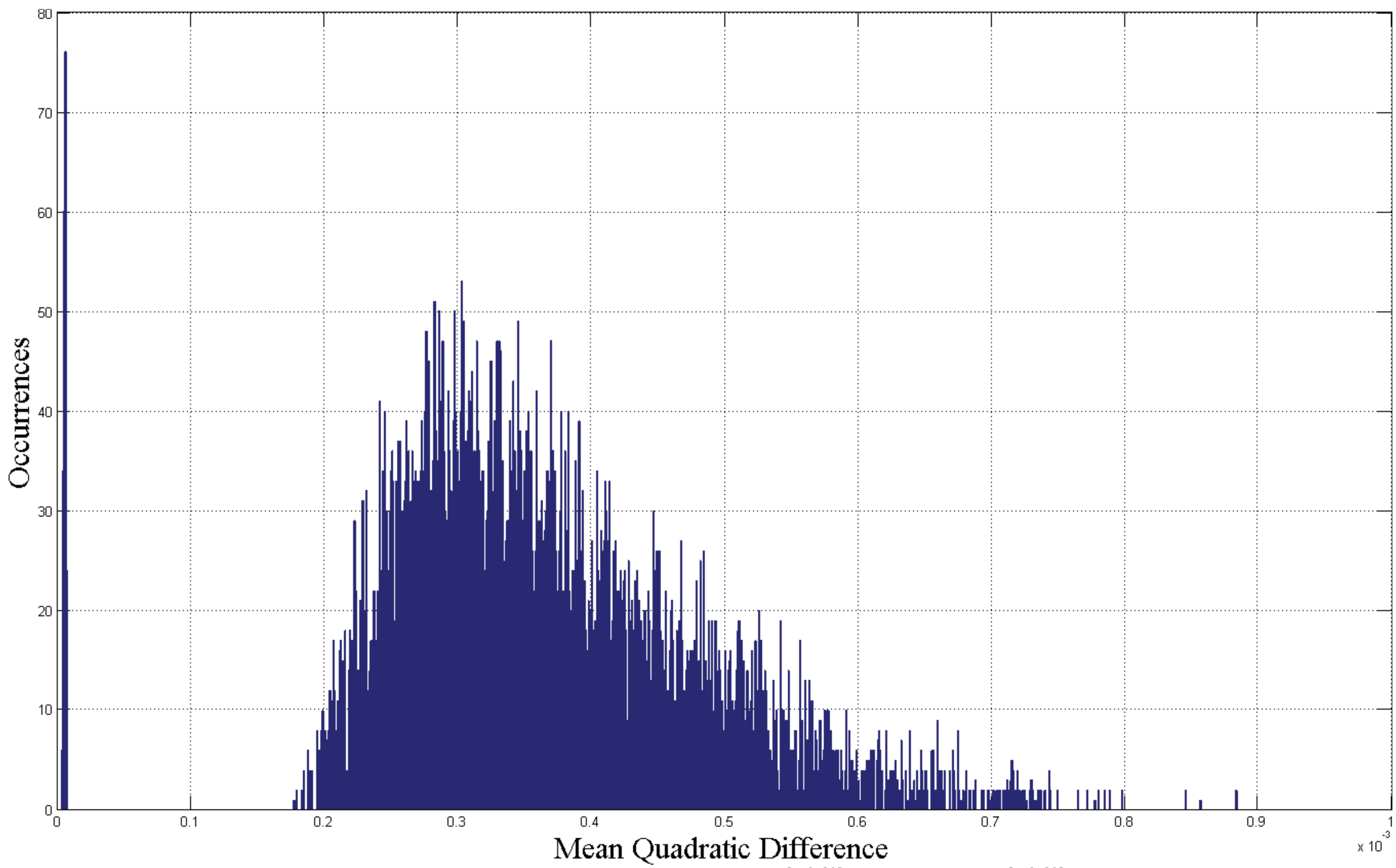

Figure 6.2 A-Law MQD Intravariability V. Intervariability

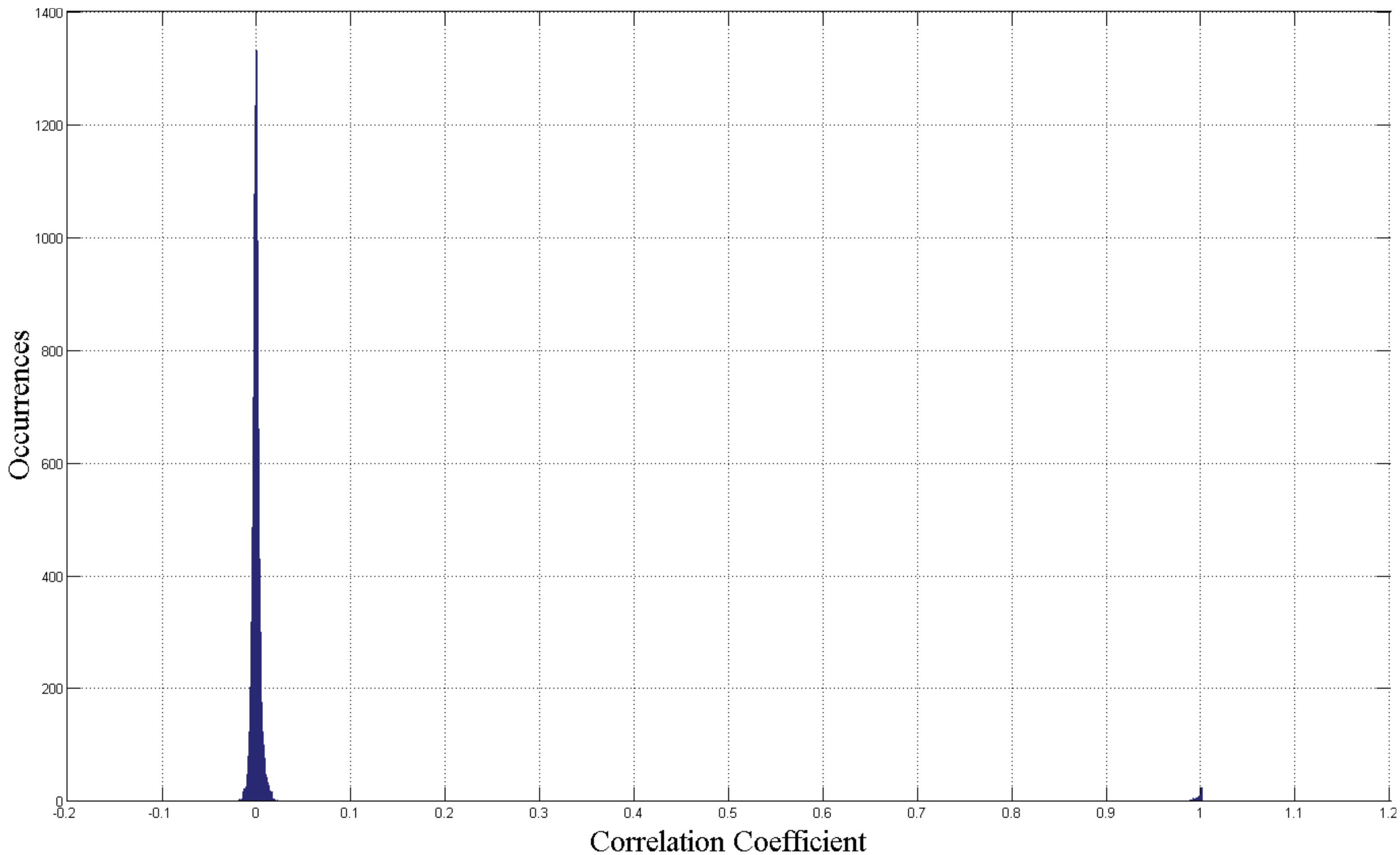

Figure 6.3 DVI ADPCM CC Intravariability V. Intervariability

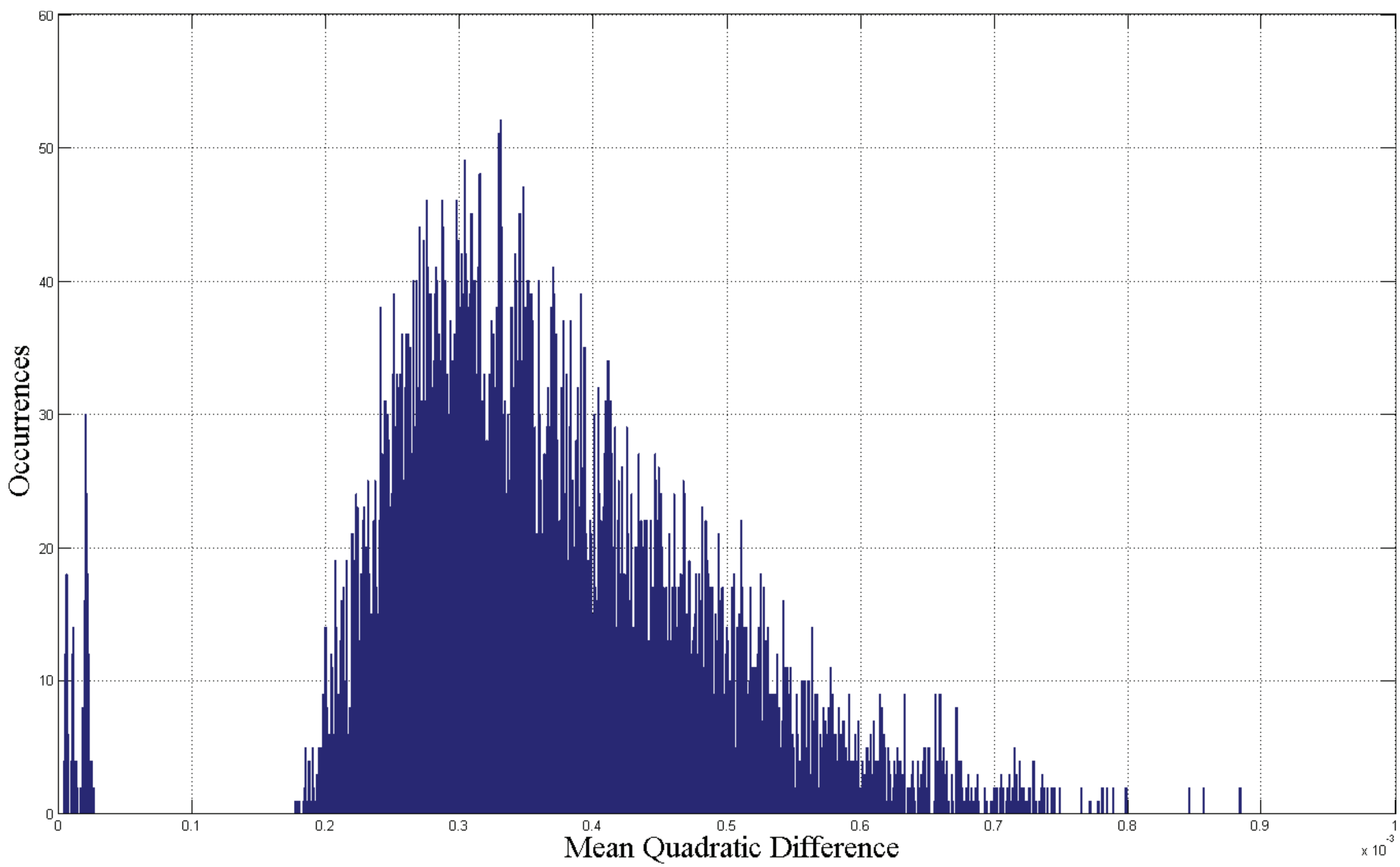

Figure 6.4 DVI ADPCM MQD Intravariability V. Intervariability

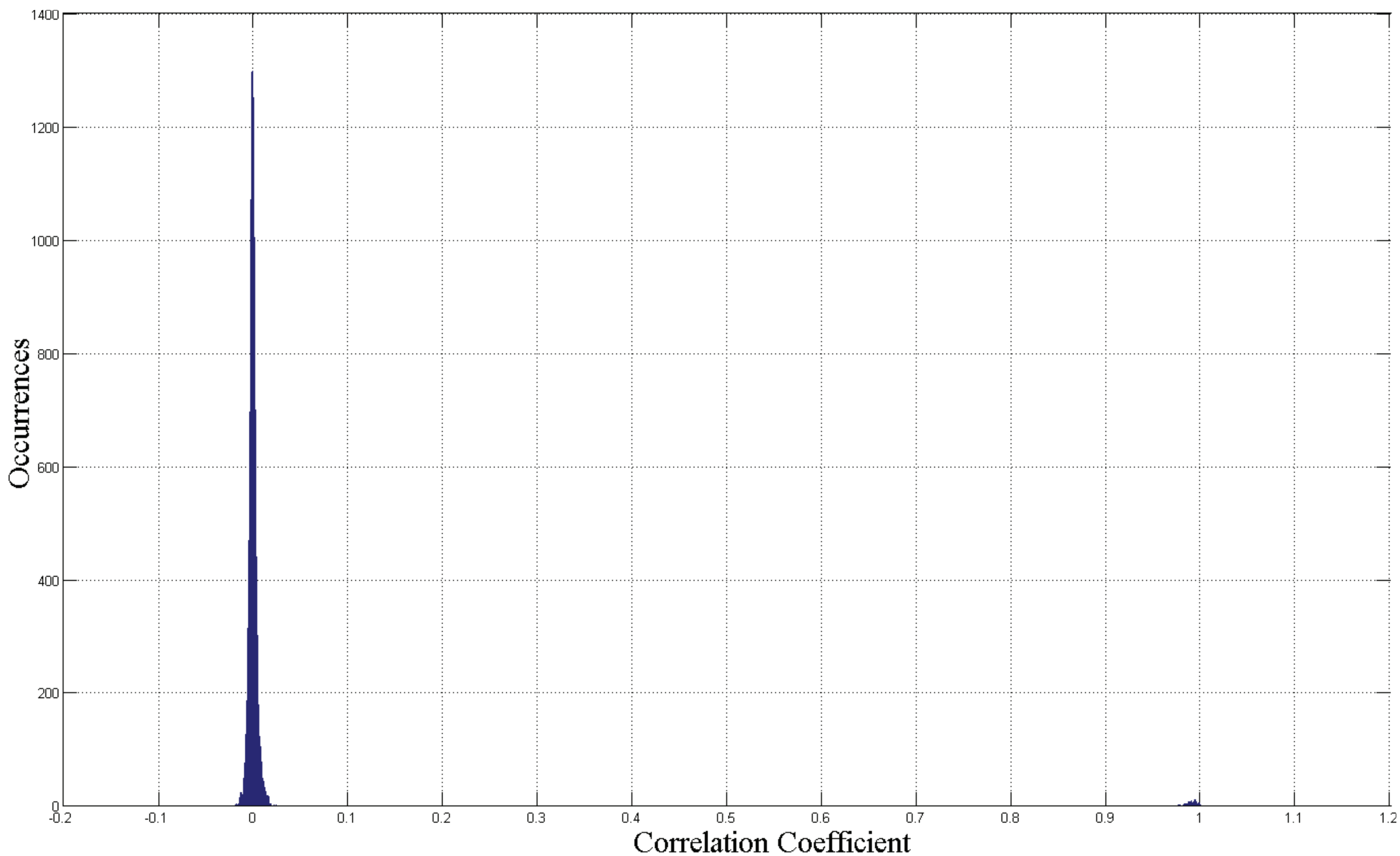

Figure 6.5 MP3 With Constant Bit-Rate CC Intravariability V. Intervariability

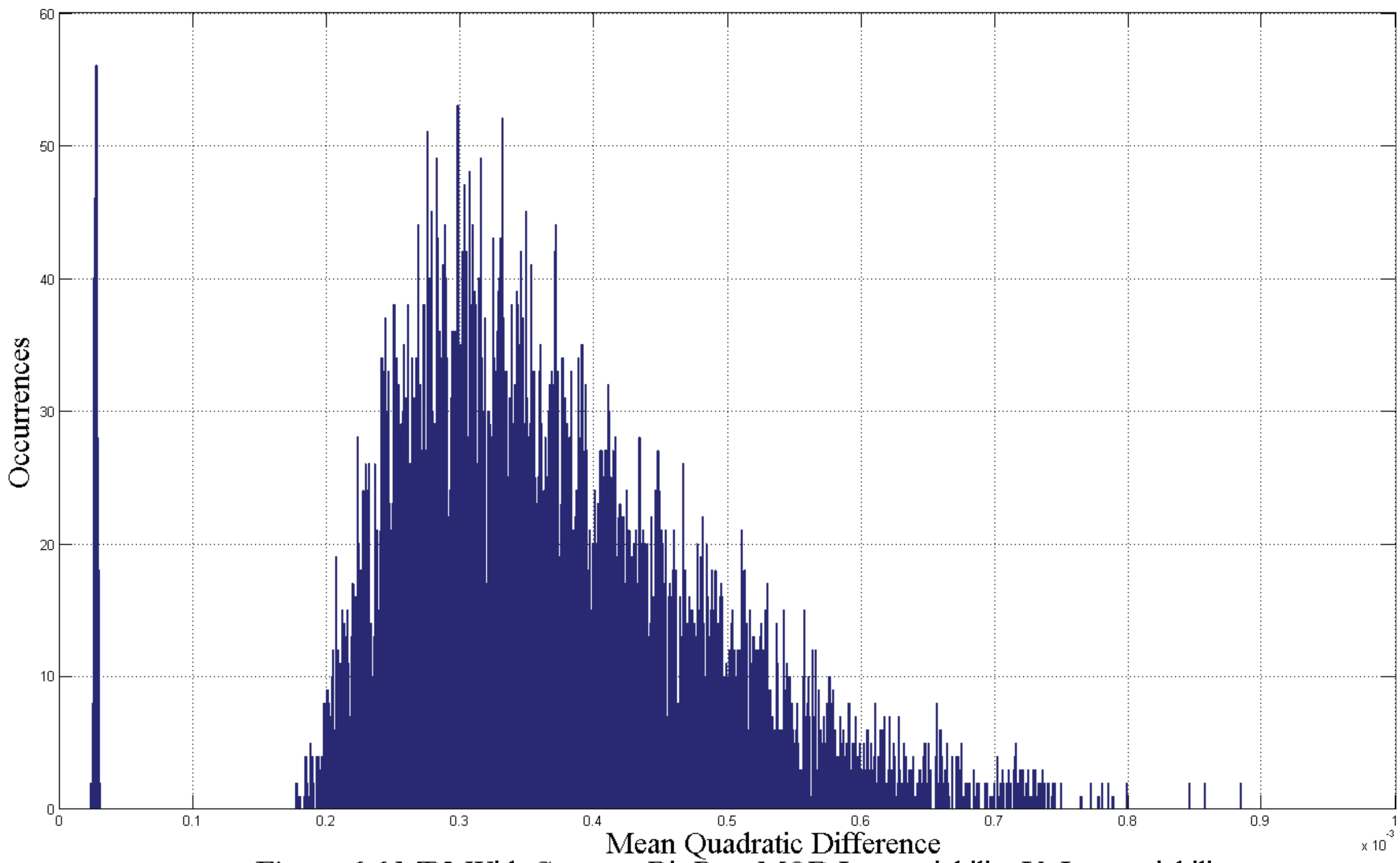

Figure 6.6 MP3 With Constant Bit-Rate MQD Intravariability V. Intervariability

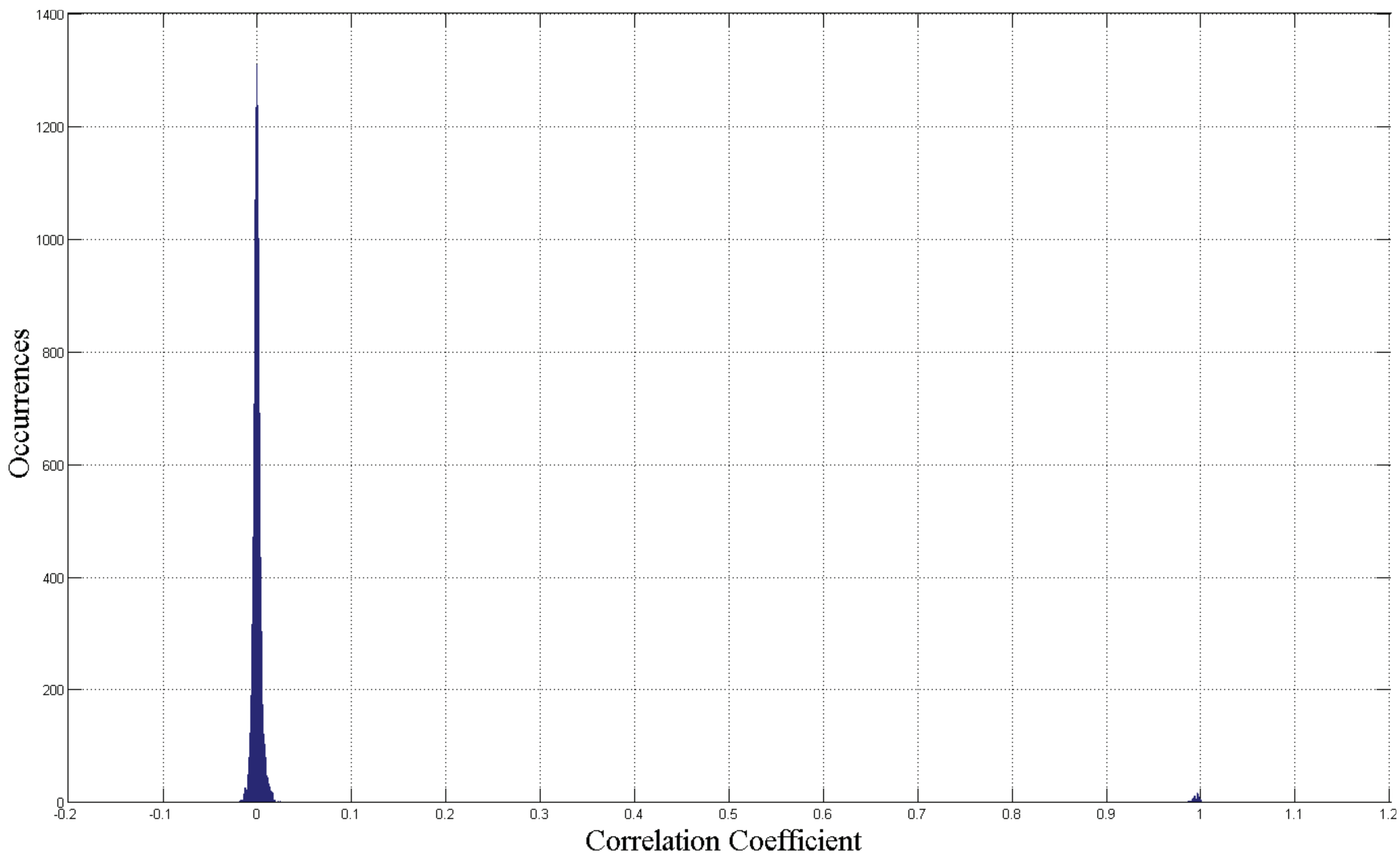

Figure 6.7 High Quality MP3 With Variable Bit-Rate CC Intravariability V. Intervariability

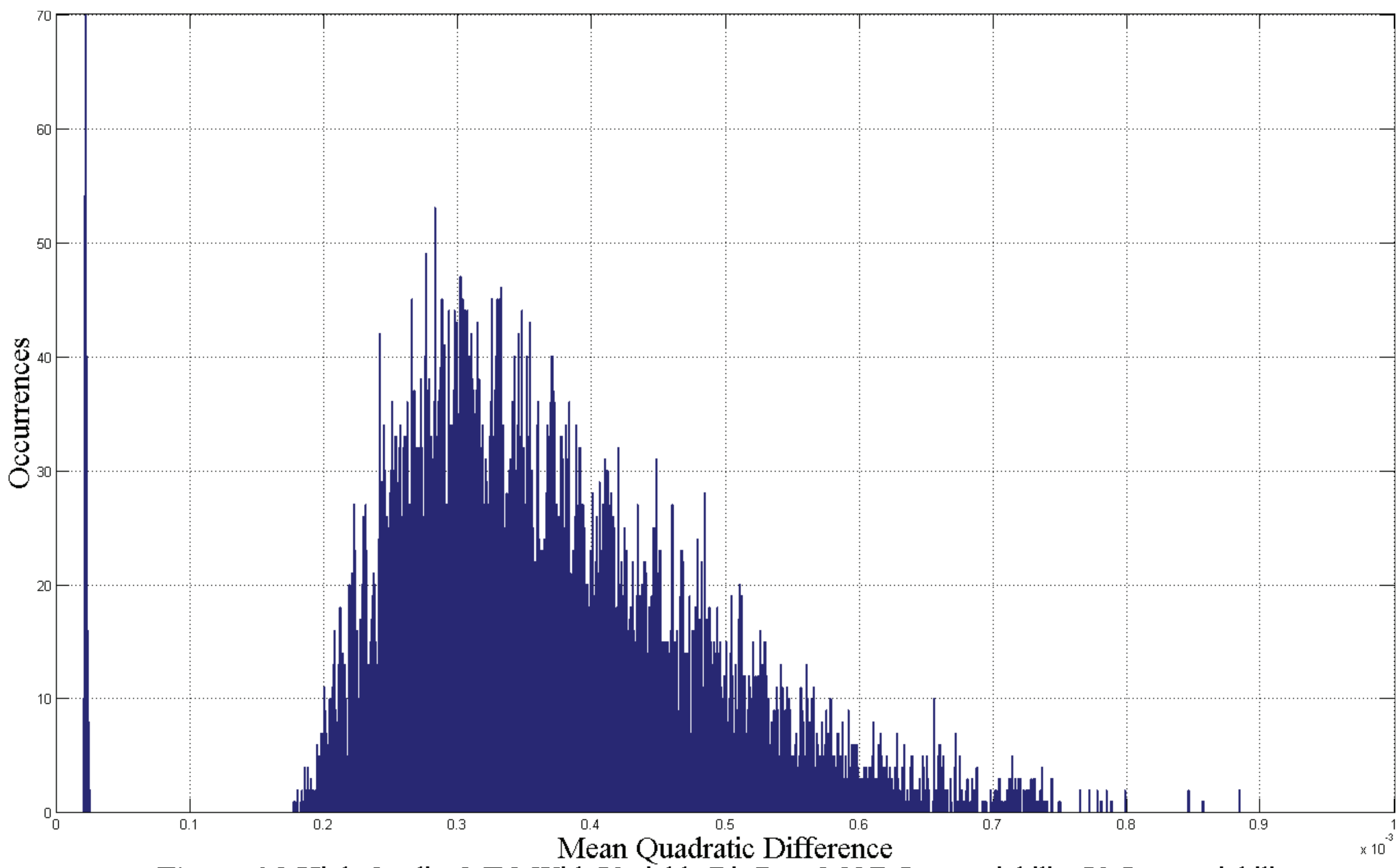

Figure 6.8 High Quality MP3 With Variable Bit-Rate MQD Intravariability V. Intervariability

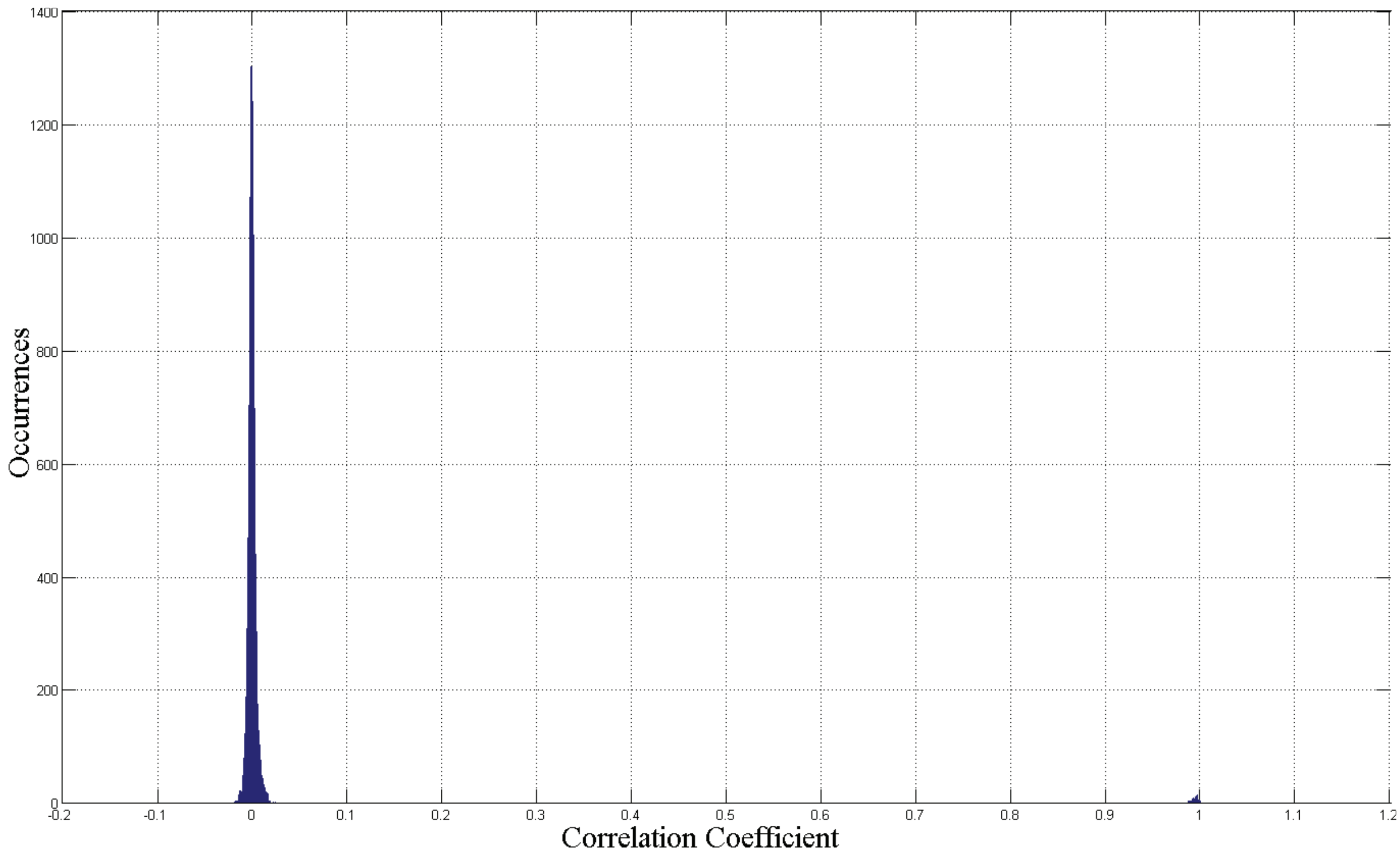

Figure 6.9 Low Quality MP3 With Variable Bit-Rate CC Intravariability V. Intervariability

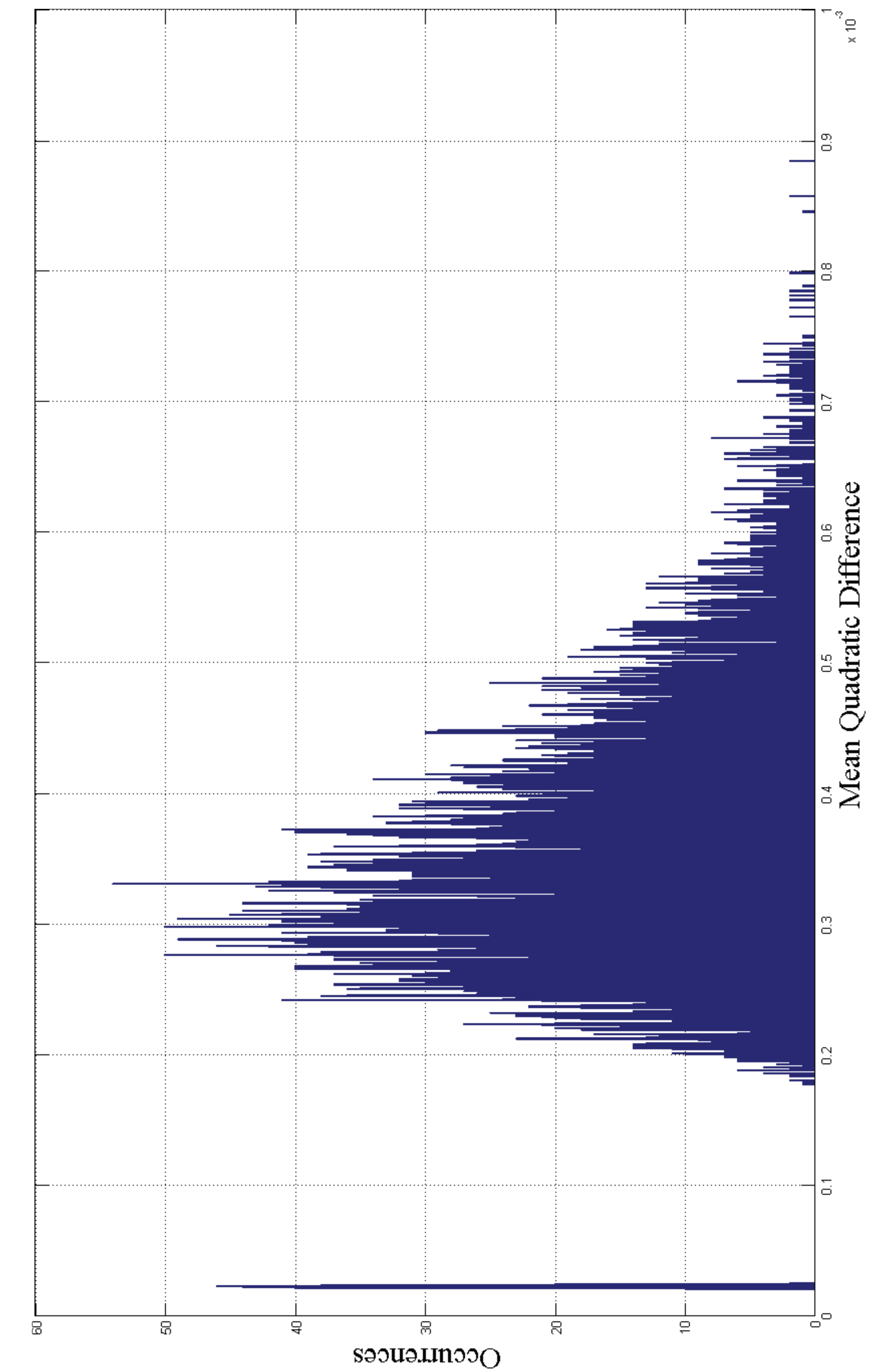

Figure 6.10 Low Quality MP3 With Variable Bit-Rate MQD Intravariability V. Intervariability

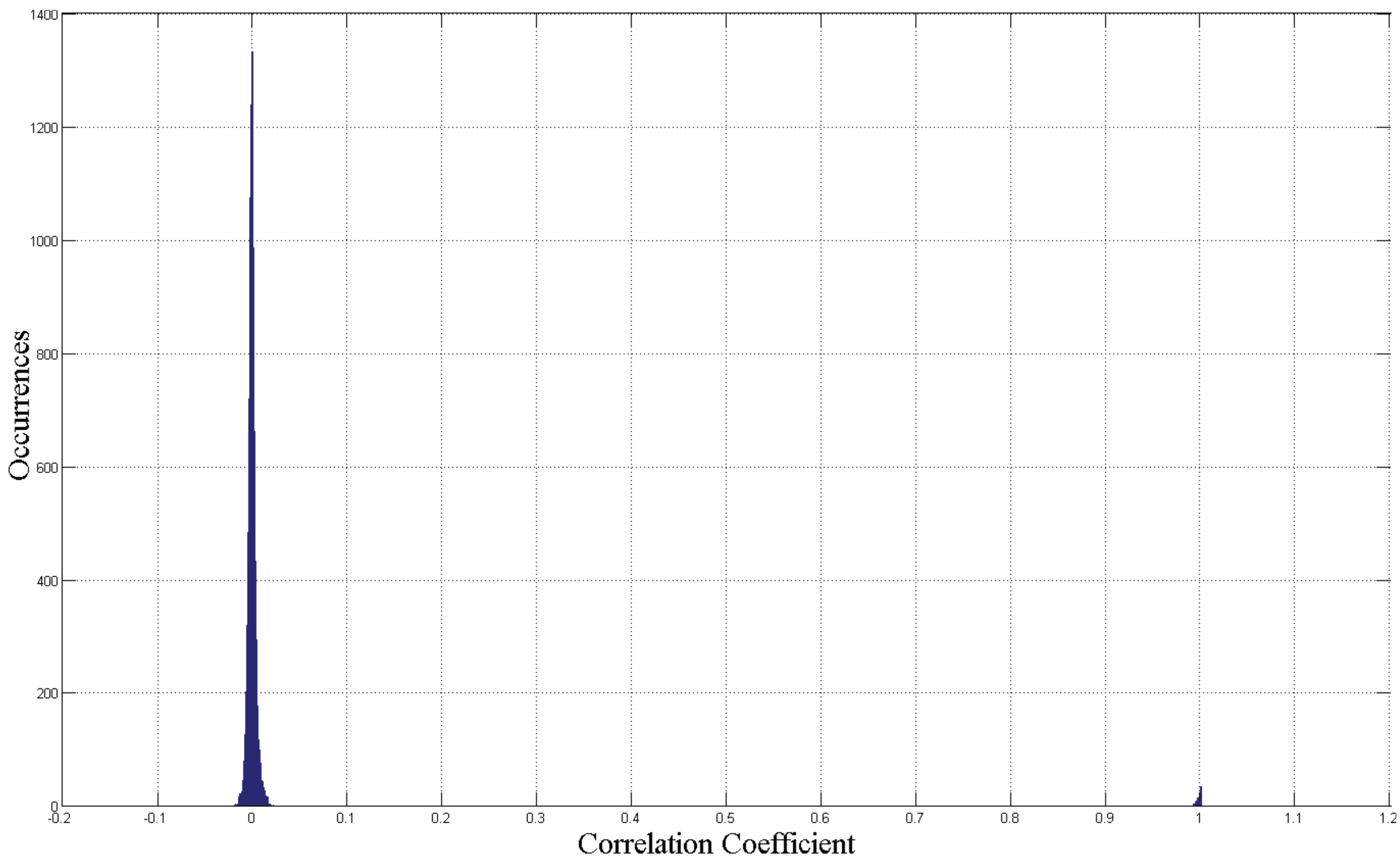

Figure 6.11 Microsoft ADPCM CC Intravariability V. Intervariability

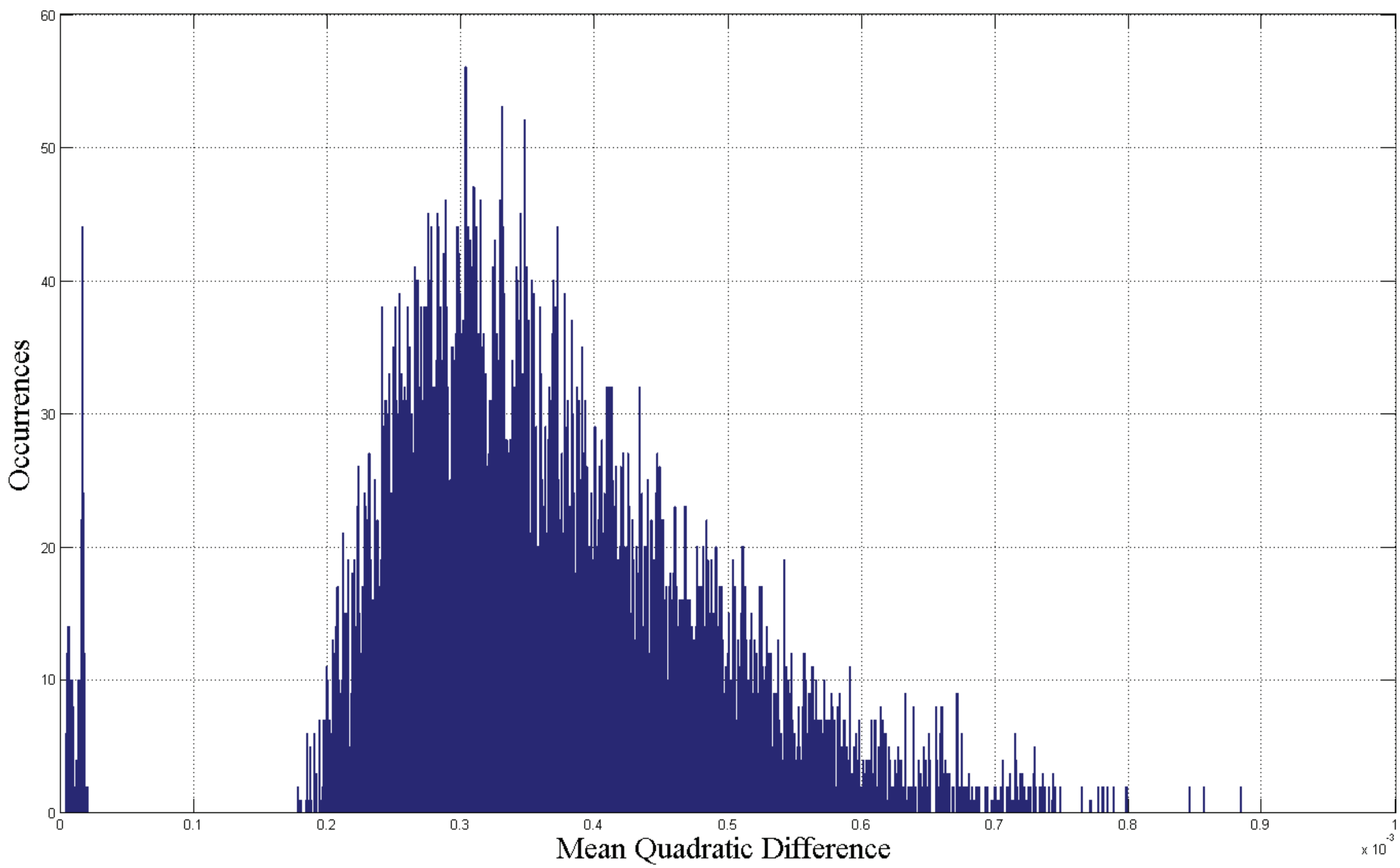

Figure 6.12 Microsoft ADPCM MQD Intravariability V. Intervariability

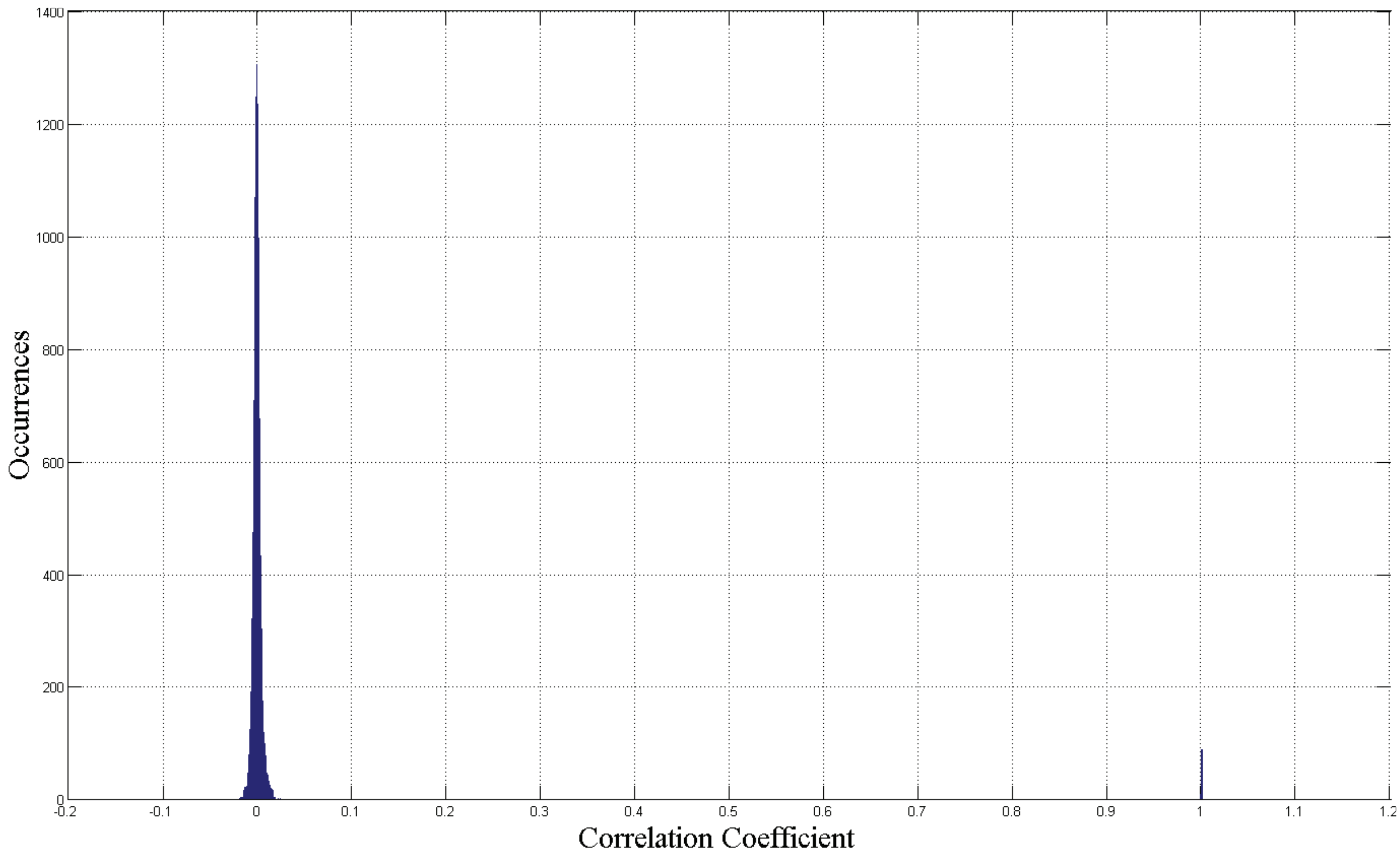

Figure 6.13 Mu-Law CC Intravariability V. Intervariability

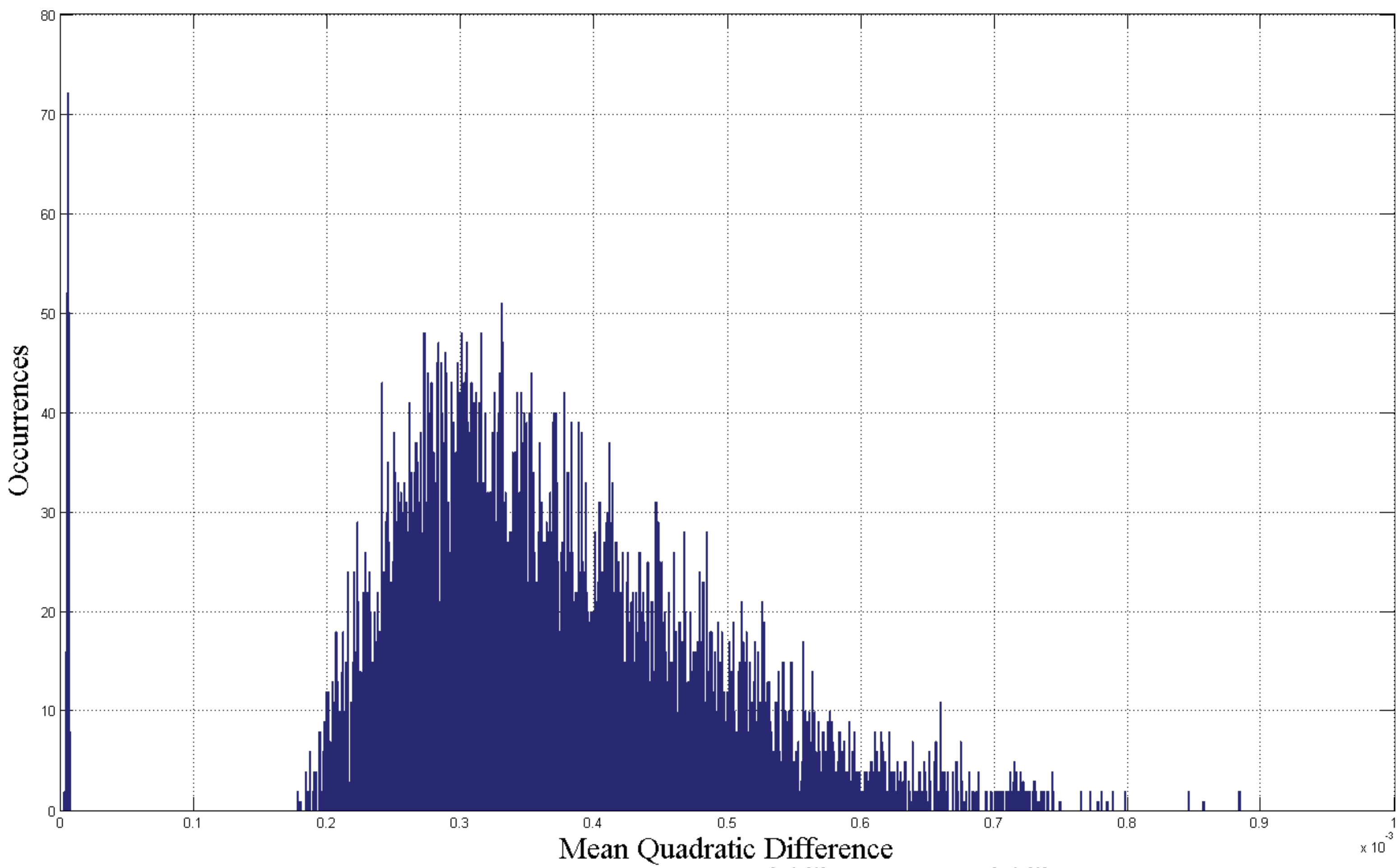

Figure 6.14 Mu-Law MQD Intravariability V. Intervariability

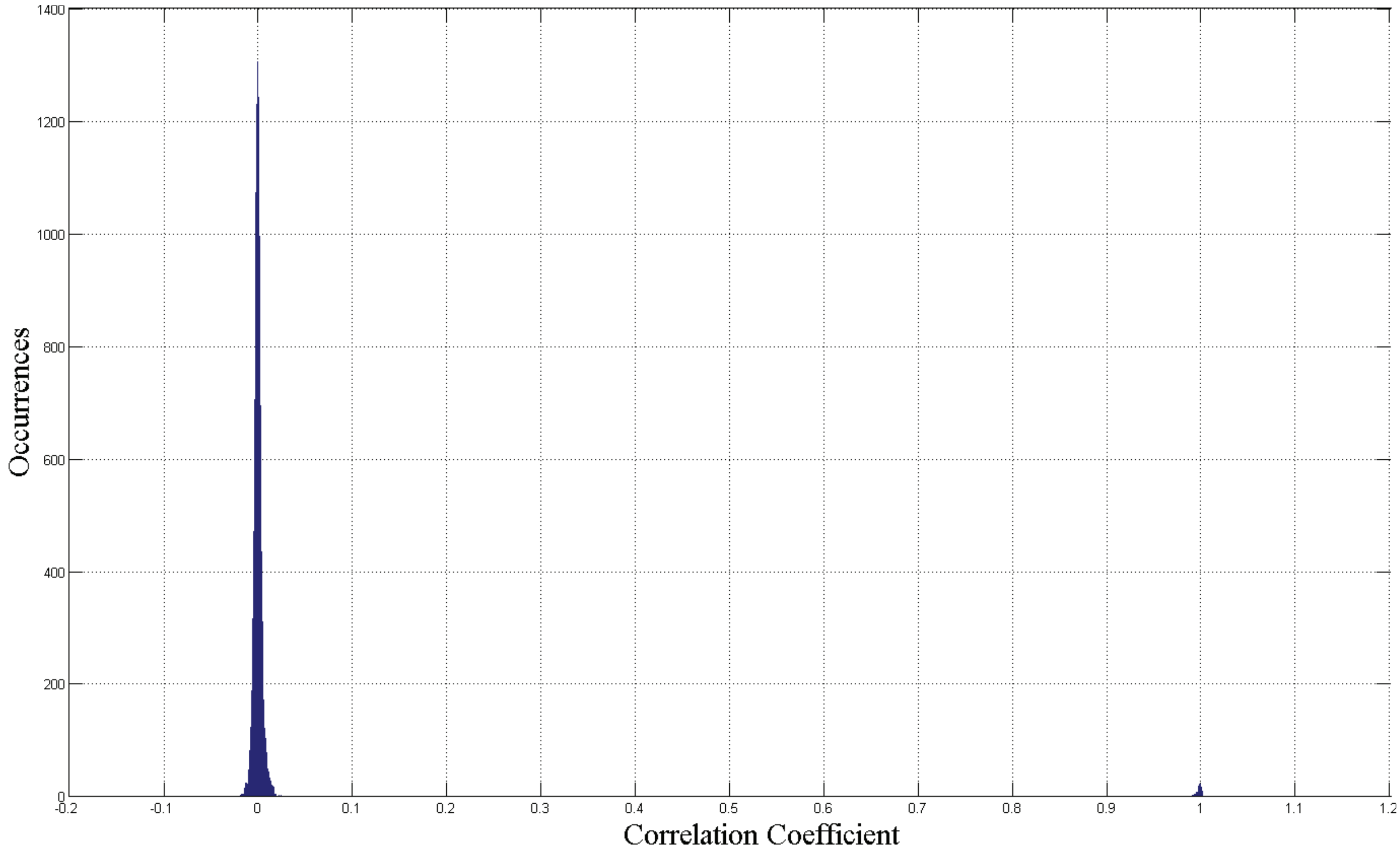

Figure 6.15 High Quality WMA With Constant Bit-Rate CC Intrvariability V. Intervariability

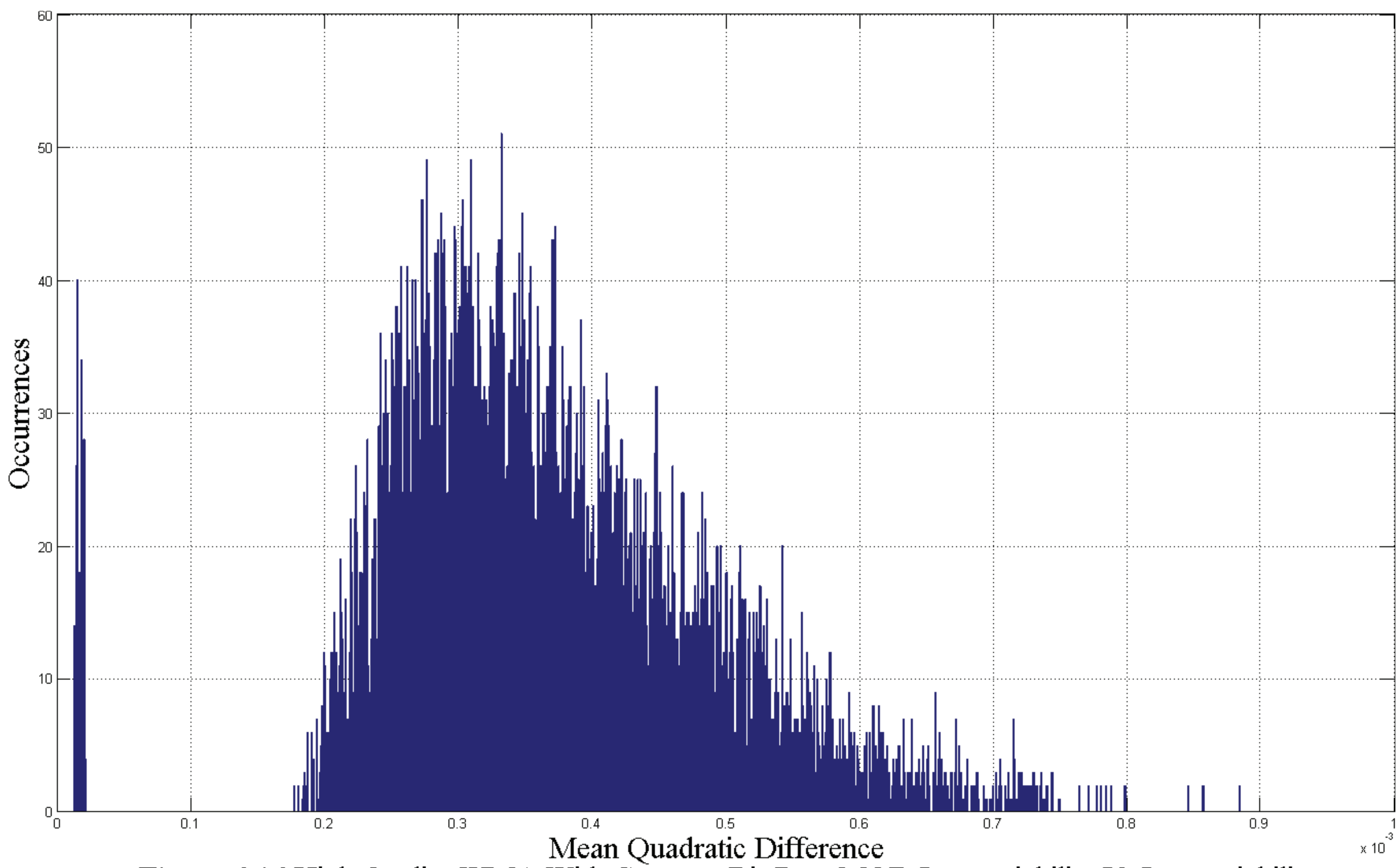

Figure 6.16 High Quality WMA With Constant Bit-Rate MQD Intravariability V. Intervariability

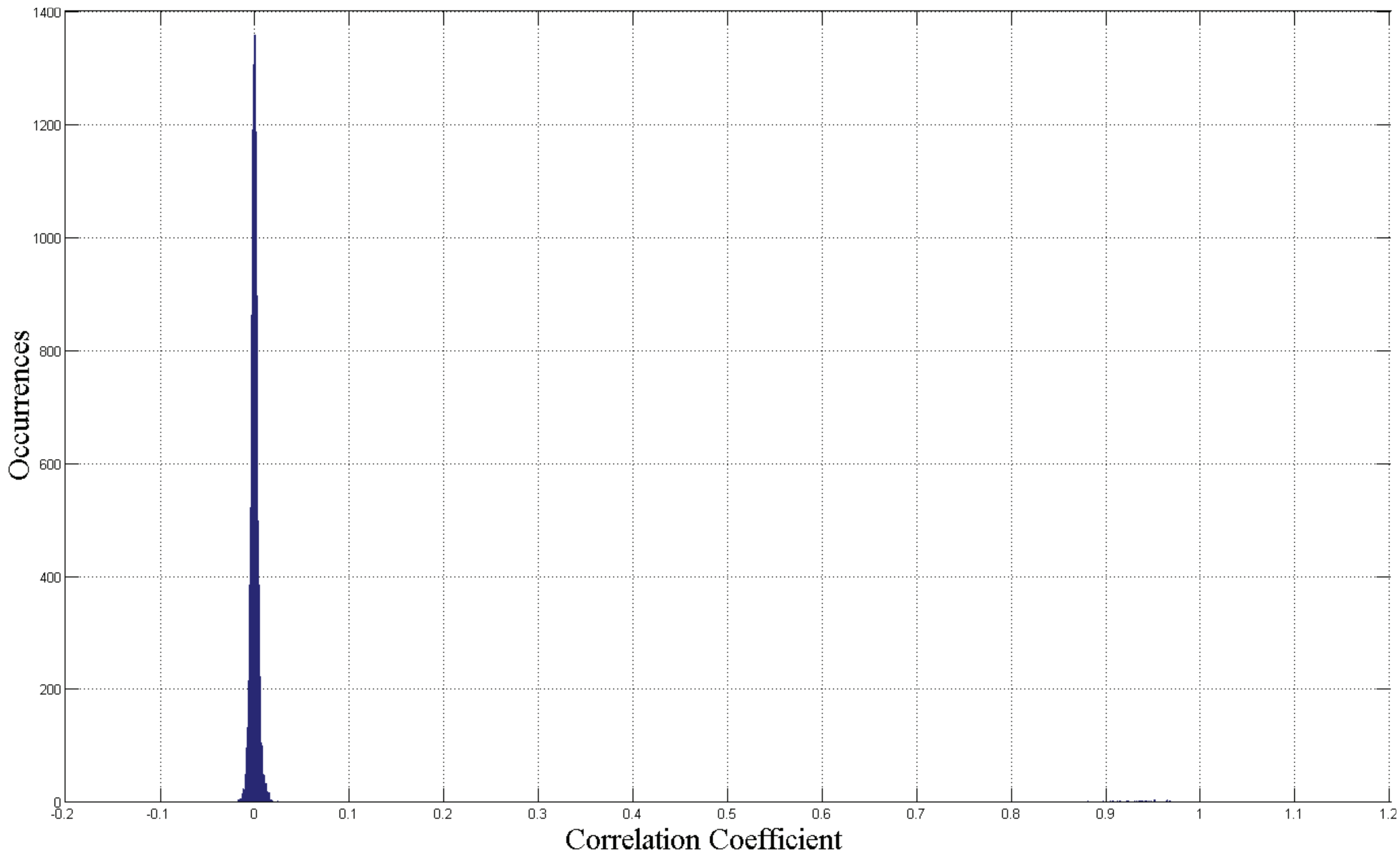

Figure 6.17 Low Quality WMA With Constant Bit-Rate CC Intravariability V. Intervariability

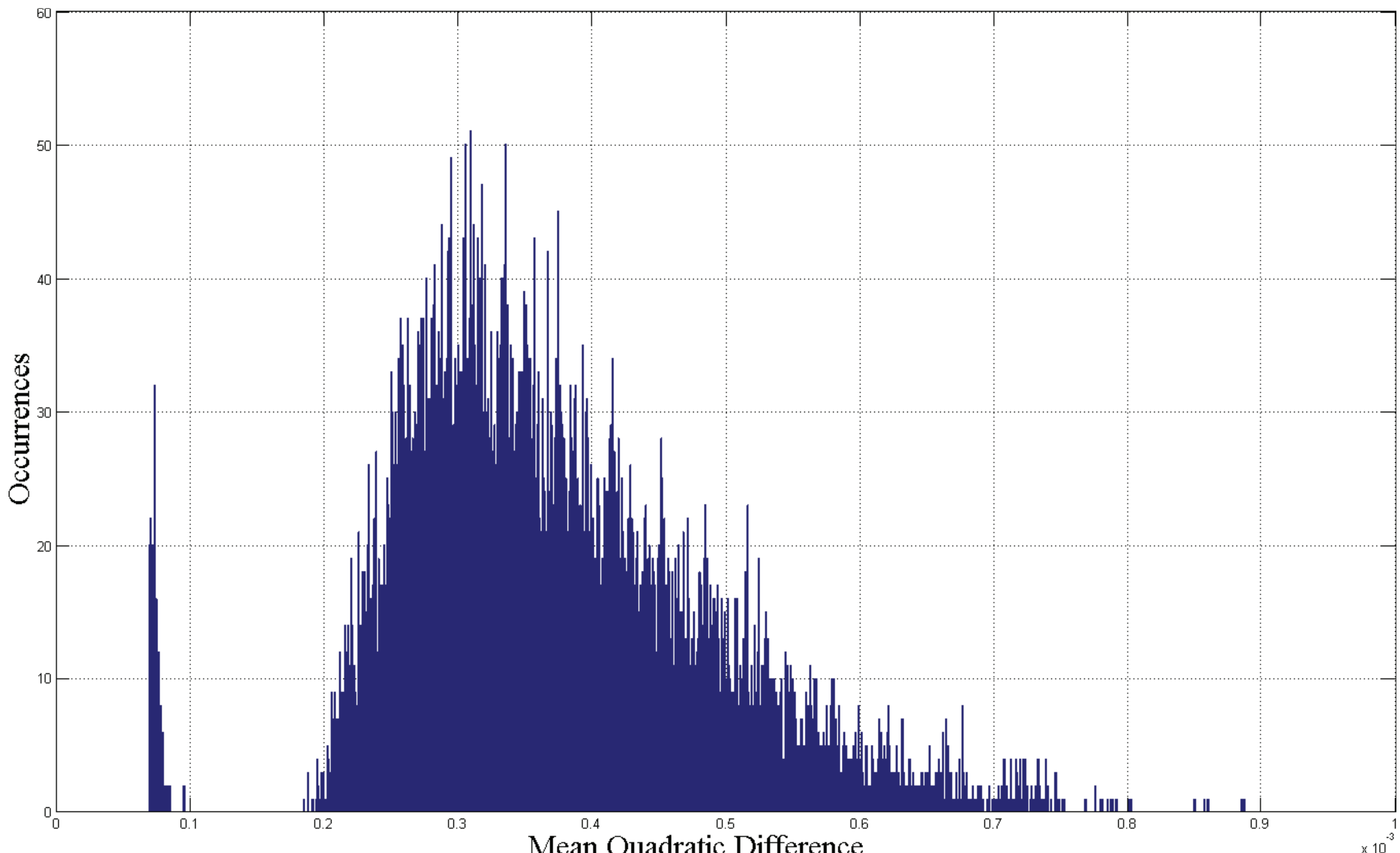

Figure 6.18 Low Quality WMA With Constant Bit-Rate MQD Intravariability V. Intervariability

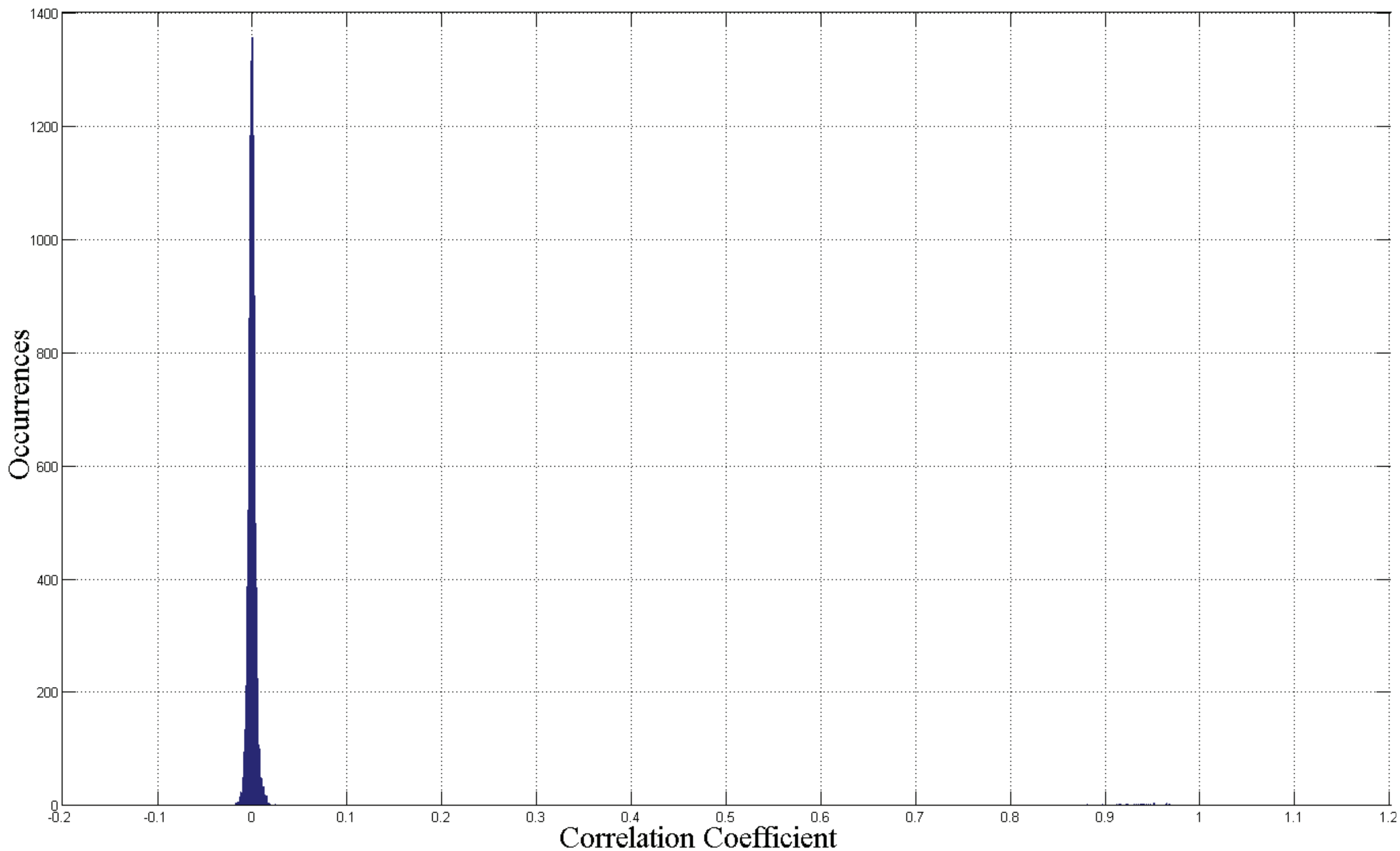

Figure 6.19 WMA With Variable Bit-Rate CC Intravariability V. Intervariability

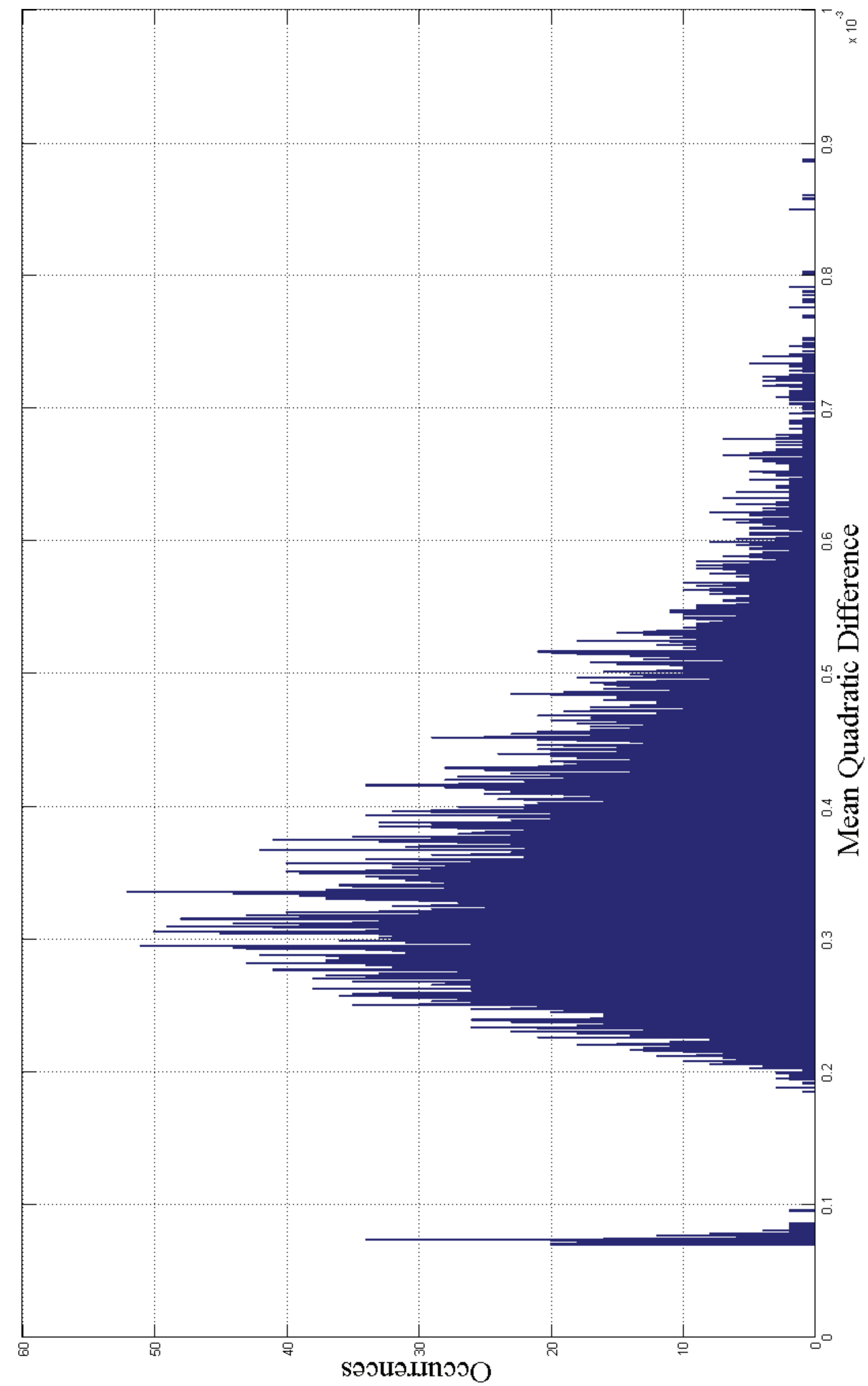

Figure 6.20 WMA With Constant Bit-Rate MQD Intravariability V. Intervariability

7. Visual Analysis

It is clear in the following figures that the ENF signal is maintained well enough by all the algorithms tested to complete a visual analysis with the procedure described in the methodology. A close look at most of the figures will reveal slight differences between the original PCM recording and the compressed formats. The differences are most obvious in the two WMA algorithms which produced the lowest correlation coefficients and the highest mean quadratic differences. Though they did not yield the greatest numbers, a visual analysis can still be successfully executed.

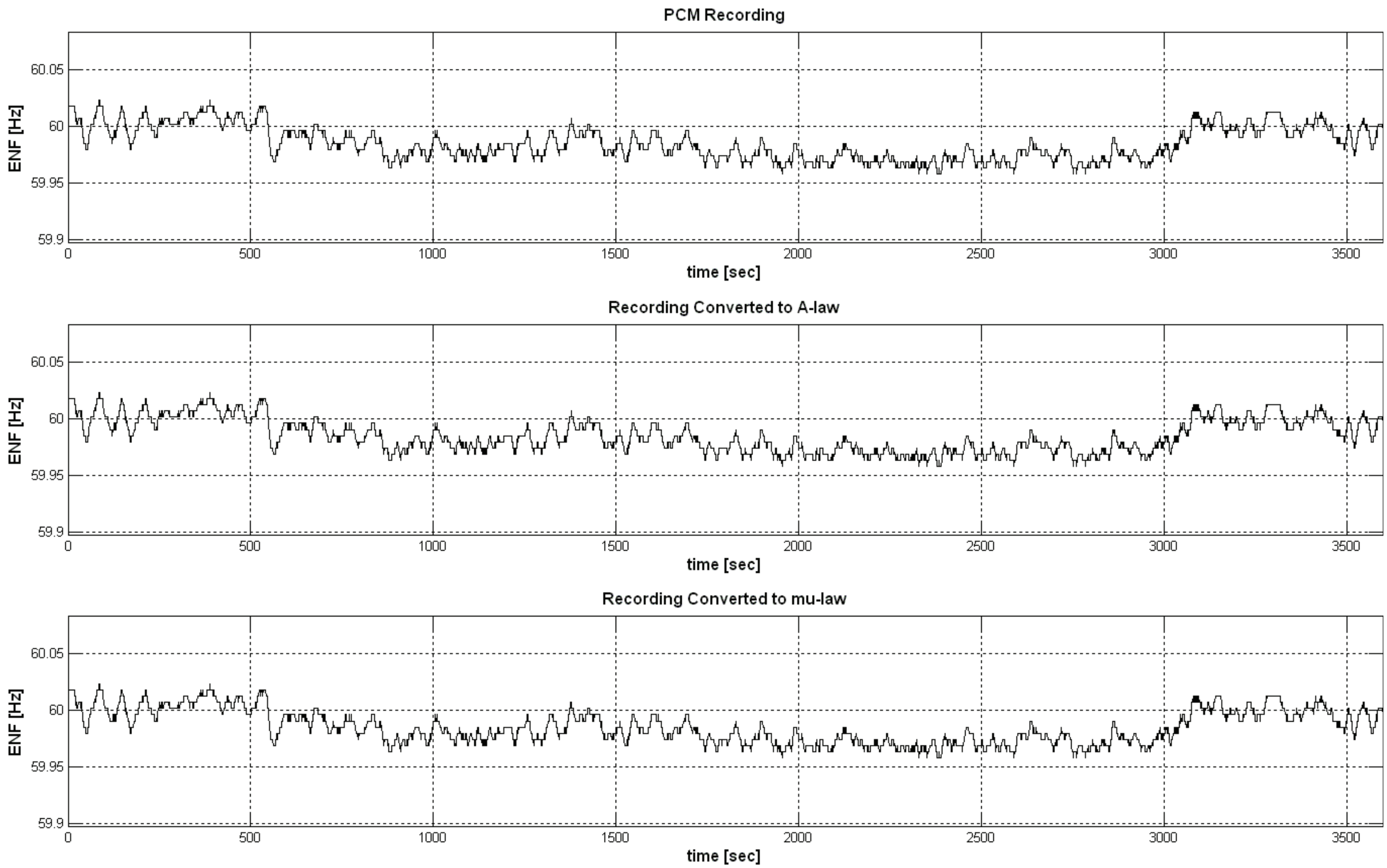

Figure 7.1 Visual Analysis For A-Law And Mu-Law

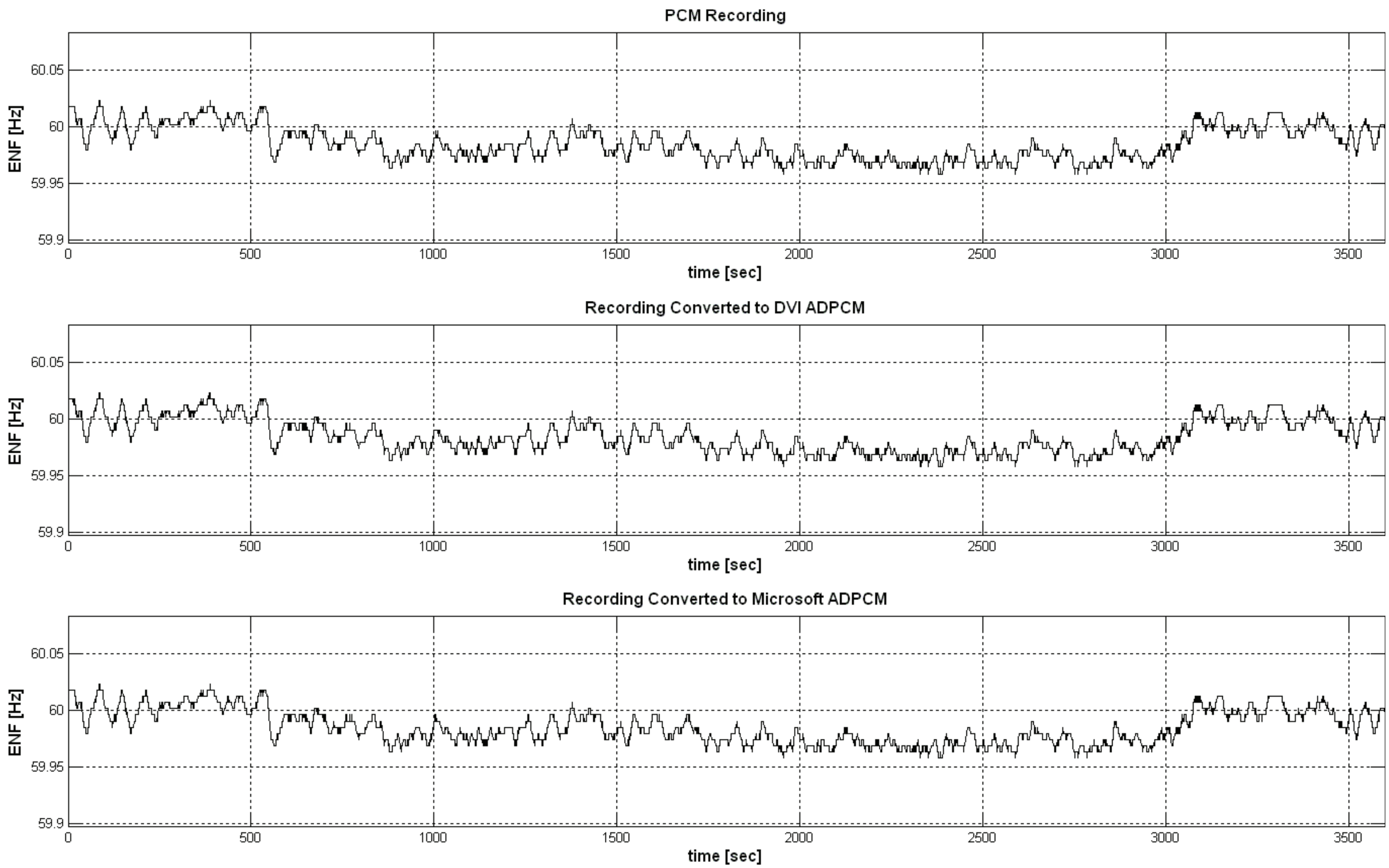

Figure 7.2 Visual Analysis For ADPCM Formats

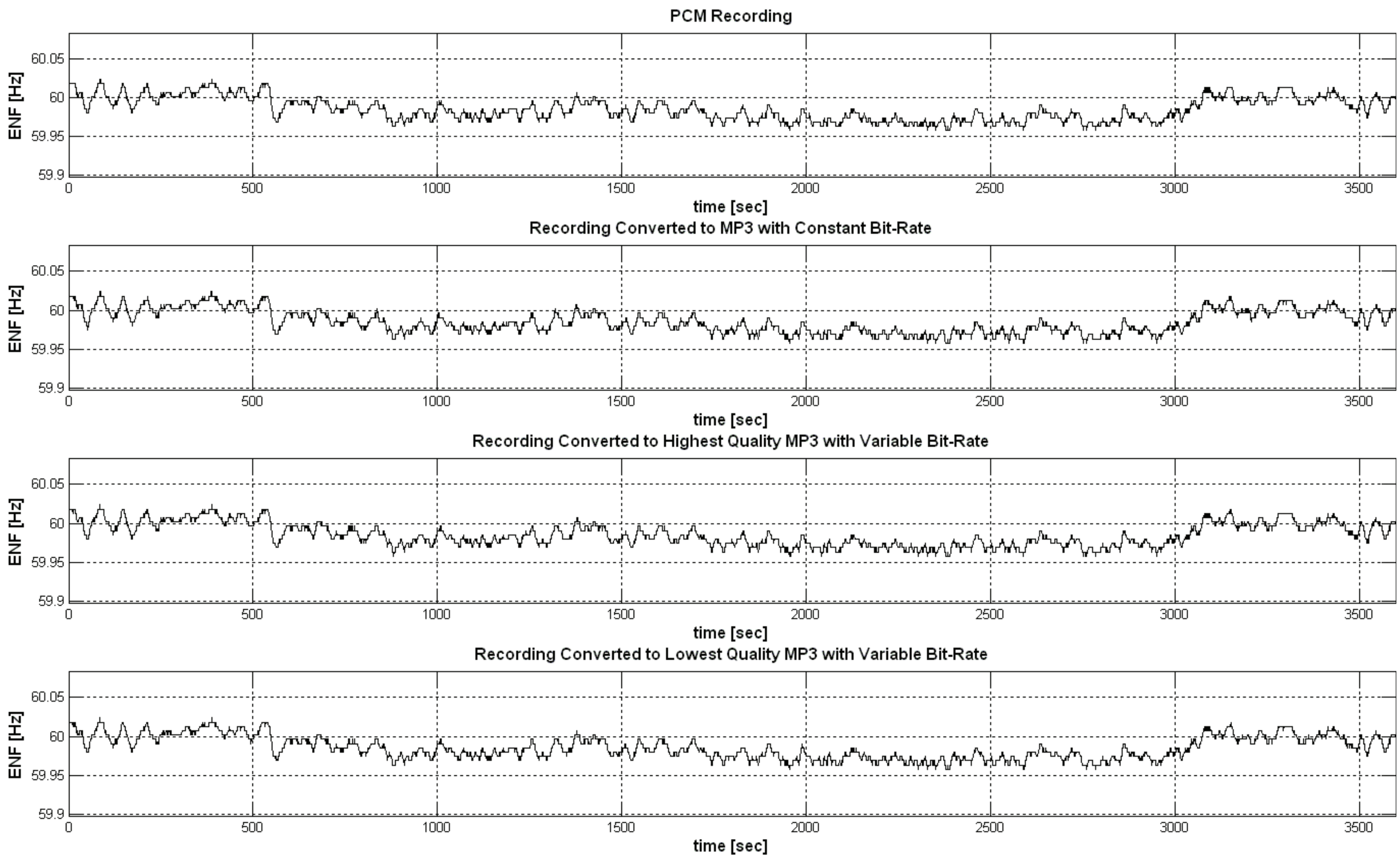

Figure 7.3 Visual Analysis For MP3 Recordings

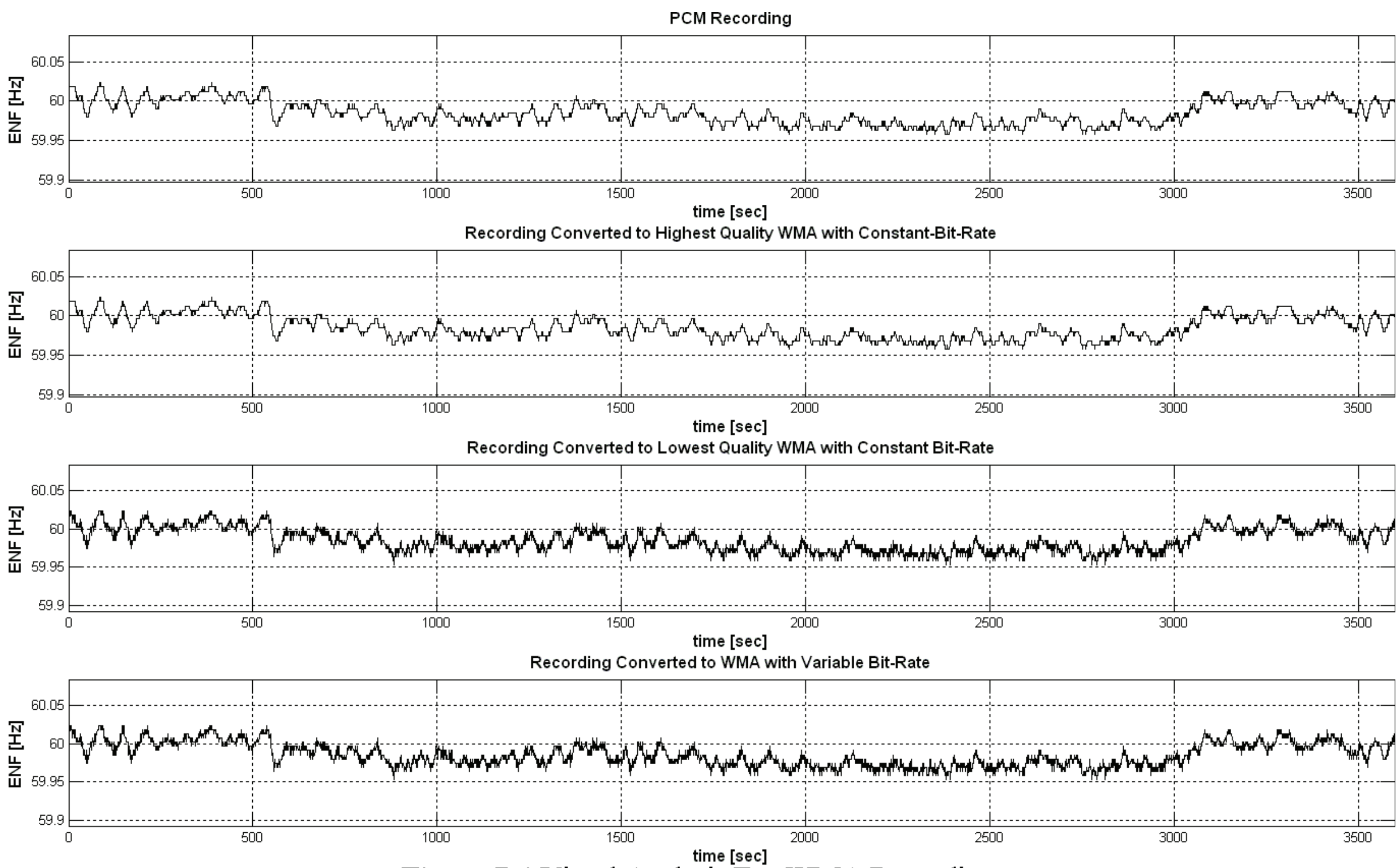

Figure 7.4 Visual Analysis For WMA Recordings

8. Discussion

Using a visual ENF analysis based on the figures produced during the ENF frequency calculations, it is possible to successfully match an ENF recording with a period of time in the ENF database even with the algorithms that performed the poorest. Of course, a forensic examiner would not normally have the opportunity to choose which algorithm is used in a forensic recording.

The ENF signal was best maintained by the A-law and mu-law algorithms. Both the A-law and mu-law algorithms had very high correlation coefficients and low mean quadratic differences. Their effect on the ENF signal was minimal and very predictable. The A-law algorithm held the highest average correlation coefficients, the lowest average mean quadratic differences, and had a lower standard deviation of correlation coefficients and mean quadratic differences than mu-law. Though these algorithms cause less degradation to the ENF signal than other algorithms, they have a lower compression ratio and therefore use more data and hard drive space than other algorithms. They are also not common compression formats in the consumer and law enforcement markets.

The ADPCM algorithms also performed well overall. Though they have a higher standard deviation of correlation coefficients and mean quadratic differences than many of the more common compression formats (especially the DVI ADPCM algorithm which produced varied results), their mean values of correlation coefficients remain high and mean values of mean quadratic differences remain low. These two algorithms, like A-law and mu-law, are also not as common in the consumer and law enforcement markets. They also have a roughly 4:1 compression ratio which results in larger files than many of the more common algorithms.

The MP3 algorithms didn't show as good of results as the algorithms which had lower compression ratios, which is to be expected. All three MP3 algorithms did produce low standard deviations of correlation coefficients and mean quadratic differences. Considering that a visual analysis is easily possible with all the MP3 algorithms, that this is one of the most common lossy compression algorithms in the world, and that they produce more predictable results than most other algorithms, the smaller file size of the MP3 algorithms may be preferred to the preceding algorithms with lower compression ratios.

Though a visual ENF analysis is possible with any of these algorithms, only one of the WMA algorithms should be recommended for use with an automated ENF analysis system. The high quality constant bit-rate WMA algorithm produced some of the better results with high correlation coefficients and low mean quadratic differences as well as being very predictable. It also yielded the smaller file size than the other two WMA algorithms, which produced drastically lower correlation coefficients and higher mean quadratic differences as well as far less predictable results than any of the other eight algorithms tested.

Though the MP3 files have the smaller standard deviations of correlation coefficients and mean quadratic differences, the actual values of the correlation coefficients and mean quadratic differences of the high quality WMA algorithm with constant bit rate show less signal degradation. Only the best MP3 correlation coefficients and mean quadratic differences have better values than the worst values for the high quality WMA algorithm with constant bit rate. Considering the high compression ratio and small file sizes as well as being one of the more common compression formats in the consumer and law enforcement markets, the high quality WMA algorithm with constant bit rate is the preferred compression algorithm in this test.

Given the use of an automated ENF analysis system (to match an audio file with a correlating period of time in an ENF database), audio files made with or converted to eight of the tested algorithms can be tested for a match with very high reliability. Automatic correlation detection should still not be questioned for the low quality WMA algorithm with constant bit-rate and the WMA algorithm with variable bit-rate; the third control study showed no overlap in the intervariability and intravariability for these algorithms. This study has shown that no forensic analysis based on the electric network frequency should be disregarded in legal proceedings solely for the reason that the audio file had been converted to any of the ten algorithms tested in this study.

A great amount of research is still to be done on ENF signals and the effects that various conditions may have on the ENF signal. This study was conducted in impeccable laboratory conditions. Future studies will include the effects of broadband noise on an ENF signal and the effects of lossy compression on an ENF signal in the presence of broadband noise. Future studies will include the use of various recording devices which have inconsistent clocks which affect the actual sample rate and induce frequency bias. Also, future studies will include the effects of recording ENF signals directly as audio files of a compressed format. Any of the aforementioned conditions may combine to have a collectively detrimental effect on an ENF signal, and these conditions will also be the focus of future studies.

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