VERSATILE EVALUATION OF EFFECTS ON DCT-BASED LOSSY COMPRESSION OF EMG SIGNALS ON MEDICAL PARAMETERS

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Abstract: Typically used simplified error measures, like mean-squared-error (MSE), do not reveal everything about the clinical quality of lossy compressed medical signals. Errors have to be interpreted via essential medical parameters. The medical parameters depend on the type of the signal and only the preservation of essential medical parameters can guarantee the correct clinical quality. In this study, short electromyography (EMG) signals are compressed with DCT transformation -based lossy compression method. The compression is gained with irreversible masking and scalar quantization of the DCT coefficients. The most prominent medical parameters of EMG signal are the mean frequency (MNF) and the median frequency (MDF). The behaviors of these parameters are studied both by fitting a regression line and by examining the mean absolute errors frequency-by-frequency over clinically interesting frequency range. This reveals the frequency dependency of errors of the medical parameters and inspires the idea that the generated linear model can be used for estimating the correct value of the processed medical parameter.

1 INTRODUCTION

The compression ratio, the computational efficiency of the method, and the quality of the result are the most essential features of lossy signal compression (Salomon, 2004). The quality of the result is typically characterized with mathematical, measurable error, or the distance between original and processed (compressed-decompressed) signal.

It has not been validated that simplified error, represented as mean-squared-error (MSE) (Carotti et al., 2006), signal-to-noise-ratio (SNR) (Cuerrero and Mailhes, 1997) or root-mean-squared difference (PRD) (Wellig et al., 1998), can establish the preservation of medical parameters. Only the preservation of essential medical parameters can guarantee the correct clinical quality. In spite of that fact, many medical signal compression studies rely only on simplified error measurements. However, some of the thorough studies have been concentrated on distinguishing proper medical parameters (Chan, Lovely and Hudgins, 1997; Carotti et al., 2006; Grönfors, Reinikainen and Sihvonen, 2006).

The lossy compression of electromyography (EMG) signals is not intensively studied, although the first methods have been published almost ten years ago (Cuerrero and Mailhes, 1997). Anyway, currently many EMG technologies, for example wireless measuring and archiving in patient recordings, need effective data compression. In this study, a DCT-based transformation approach has been used (Cuerrero and Mailhes, 1997; Berger et al., 2003), because of well-known algorithm with efficient implementation.

The most prominent spectral features of EMG signal are the mean frequency (MNF) and the median frequency (MDF) (Farina and Merletti, 2000; Filligoi and Felici, 1999), whose time evolution has been used for clinical assessment of EMG recordings. The simplified error represents a suggestive average estimate of the error value of the medical parameters, but it cannot be used to predict where in the dynamic range the error has been concentrated. In this study, we focus on versatile evaluation of compression effects on medical parameters. Both systematic and random errors on medical parameters are examined over these dynamic ranges.

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2 MATERIALS AND METHODS

We have used real EMG recordings in this study. All the tests and simulations were done with Matlab (Versions 6.5.0.180913a Release 13 and 7.14 Release 14).

2.1 Test Signals

We have used EMG signals measured from paraspinal muscles of healthy young volunteers. The measurements and classification were done by an experienced clinical neurophysiologist. The duration of every signal was 20 seconds and they were sampled with 1 kHz sampling frequency, consisting of 20000 twelve-bit integer values measured with DCU-600 lightweight EMG system (Sihvonen et al., 2004). Each signal consists of several muscle activity periods.

We have randomly picked out five 20000 sample long EMG signals for training material and another five 20000 sample long EMG signals for testing material. On other words, we have used two independent materials for testing and training, both consisting of 100000 samples.

2.2 Spectral Features Mean Frequency and Median Frequency

The mean and median frequencies are calculated from the frequency spectrum of the segmented signal. Signal segments are sliding over the signal with one sample step (segments are heavily overlapping). The frequency spectrum is obtained by taking the FFT of the segment, using a Hanning window of length 1024. The frequency spectrum consists of 512 amplitude coefficients, A_i.

The mean frequency MNF is the amplitude-weighted average of the frequencies,

$$MNF = \frac{\sum_{i=1}^{M} f_i A_i}{\sum_{i=1}^{M} A_i} \tag{1}$$

Graphically, the median frequency is the frequency dividing the area of the amplitude spectrum into equal halves. The value can be computed using a cumulative function

$$c_{fk} = \frac{\sum_{m}^{f_k} A_m}{\sum_{m} A_m} \tag{2}$$

The median frequency MDF is the value of f_k for which the value of c_{fk} is as close to 1/2 as possible.

2.3 The DCT Method

The proposed compression technique is based on discrete cosine transformation which is a very popular transformation used in many compression schemes, especially in image compression standards such as JPEG. There are also applications for biomedical signal compression based on DCT (Cuerrero and Mailhes, 1997; Berger et al., 2003). The idea of transformation coding is that the sequence of *n* data samples of one domain is rotated to some other domain with equation

$$\mathbf{X} = \mathbf{TY} \tag{3}$$

where **X** is the vector of original signal coefficients, **Y** is the vector of transformed coefficients and **T** is the transform matrix. The DCT coefficients of *n* data samples in one-dimensional case is (Salomon, 2004) given by

$$G_f = \sqrt{\frac{2}{n}} C_f \sum_{t=0}^{n-1} p_t \cos\left[\frac{(2t+1)f\pi}{2n}\right] \tag{4}$$

where

$$C_f = \begin{cases} \frac{1}{\sqrt{2}}, & f = 0, \\ 1, & f > 0, \end{cases} \quad for \quad f,t = 0,1,\ldots,n-1. \tag{5}$$

Input vector of *n* data values is p_t and the output vector is a set of *n* DCT coefficients G_f. The inverse DCT transformation is (Salomon, 2004) given by

$$p_t = \sqrt{\frac{2}{n}} \sum_{j=0}^{n-1} C_j G_j \cos\left[\frac{(2t+1)j\pi}{2n}\right], \quad for \quad t = 0,1,\ldots,n-1. \tag{6}$$

DCT compression concentrates signal energy to a small number of DCT coefficients and the compression is usually achieved by eliminating the coefficients containing less information.

The DCT method applied here is based on three steps:

- DCT
- Eliminating some of DCT coefficients by using a masking vector
- Scalar quantization of the coefficients

First step was to calculate DCT from the original signal using blocks of 16, 24 or 32 signal coefficients. In these tests DCT was done by using MatLab's DCT-function. After that, some of the coefficients were eliminated by using binary maskvector. Maskvector is the same size as the used DCT block size. If maskvector's value in some index is zero, the value of corresponding index of DCT block will be eliminated. Otherwise maskvector's value is one and DCT coefficient in corresponding index will not be eliminated.

Maskvector is constant during the whole compression process and the same vector is used when compression is done and when signal is decompressed. Before IDCT, receiver adds zeros at those indexes of DCT block where coefficients have been eliminated to have correct number of reconstructed signal coefficients.

In this study, we have used masking to eliminate high end DCT coefficients. For block size 16 coefficients we masked out last 3, 5 and 7 DCT coefficients, for block size 24 respectively 4, 8 and 12 DCT coefficients, and for block size 32 respectively 5, 10 and 15.

After masking the selected coefficients, the rest of coefficients will be scalar quantized. Compression in this method comes from masking some DCT coefficients and from scalar quantization.

Decompression is done by finding the DCT values corresponding to indexes from codebook, adding zeros to those places of the DCT block where coefficients have been eliminated and making the IDCT.

2.4 Scalar Quantization of Coefficients

In this study, non-uniform scalar quantization method was used to quantize the DCT coefficients. In a uniform scalar quantization the difference between every value in codebook is the same, whereas in a non-uniform scalar quantization the difference between codebook values depends on the distribution of coefficients' probabilities. In the intervals where the probability of that the coefficient is placed on that interval is large, the difference between codebook values is short, and where the probability of coefficient is placed on some interval is small, the difference between codebook values is bigger.

Table 1: Raw remaining sizes and mean-squared-errors (MSE) of compressed signals in percentages by variations.

Codebook size 64 (6 bit)		
Segment length 16 samples		
Without mask	50%	25.6498
Masking last 3	41%	25.9935
Masking last 5	34%	27.6196
Masking last 7	28%	36.1951
Segment length 24 samples		
Without mask	50%	17.0290
Masking last 4	42%	17.2294
Masking last 8	33%	19.0580
Masking last 12	25%	36.3946
Segment length 32 samples		
Without mask	50%	19.5787
Masking last 5	42%	19.7208
Masking last 10	34%	20.8712
Masking last 15	27%	31.1169
Codebook size 256 (8 bit)		
Segment length 16 samples		
Without mask	67%	20.2835
Masking last 3	54%	20.6467
Masking last 5	46%	22.2934
Masking last 7	38%	30.9039
Segment length 24 samples		
Without mask	67%	13.6706
Masking last 4	56%	13.8864
Masking last 8	44%	15.7420
Masking last 12	33%	33.1424
Segment length 32 samples		
Without mask	67%	18.4853
Masking last 5	56%	18.6404
Masking last 10	46%	19.8118
Masking last 15	35%	30.1023

We constructed the codebooks by using Matlab's KMEANS function. Before using KMEANS function, the DCT of the training signal was calculated using the same DCT block size which will be used when compressing the test signal. KMEANS function was given the following parameters: training signal, which has 50000 samples, replicates 'rep' was 3, which made method more optimal, maximum number of iterations 'maxiter' was 800 and 'EmptyAction' was 'singleton', which creates a new cluster consisting of the one point furthest from its centroid. We tested codebook sizes 64 and 256. For codebook size 64, it is possible to present all codebook indexes with 6 bits and respectively for codebook size 256, indexes are presented with 8 bits.

3 RESULTS

The transformation itself has no compression effect; all the compression is gained with irreversible masking and scalar quantization of DCT coefficients.

The achieved compression rations and related MSE values by processing variations are listed in Table 1. The general observation is that the MSE increases when more coefficients are masked out and MSE decreases when codebook size increases.

3.1 The Parameter Model

The mean frequency and median frequency values are calculated from sliding segments for original testsignal and all compressed-decompressed signals. In every case we got 98974 MNF, MDF -pairs from every signal. These values are compared time synchronically against values of the original unprocessed test material. That way we got new set of value pairs:

$$\left(MNF_i^{original}, MNF_i^{processed}\right)$$
$$\left(MDF_i^{original}, MDF_i^{processed}\right) \qquad (7)$$

where $i = 0,...,98973$ is the segment number.

The pairs of values make possible the evaluation of the effects of lossy compression to essential medical parameters from-frequency-to-frequency. In an ideal case, there are no differences.

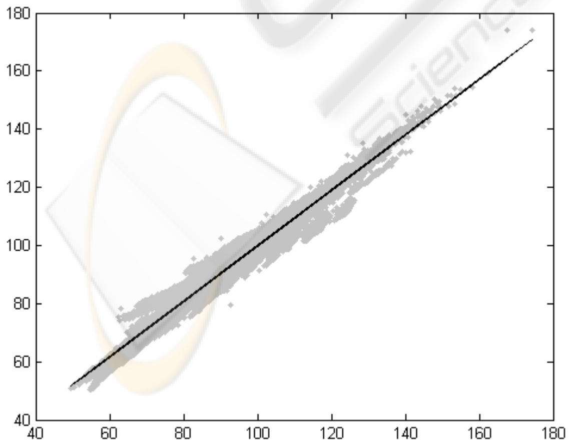

Figure 1: Idea of fitting the regression line.

To model the behaviour of original MNF and MDF values against the processed values, we fit the regression lines to all sets with Matlab's POLYFIT function.

$$MNF^{processed} = aMNF^{original} + b$$
$$MDF^{processed} = cMDF^{original} + d \qquad (8)$$

In Figure 1, the best fit line can be seen inside the cloud of data points. Both axes are in frequency (Hz) and the points are presented as the original value on X-axis against the processed value on Y-axis. The line coefficients and the norm of residuals are listed in Table 2 - 5. If the line is exactly diagonal, there is no error between the medical parameters of original and processed signals.

The error of MNF value is typically positive in low frequencies (the MNF of processed signal is higher than the MNF of the original signal) and negative in high frequencies. Reversal point is around 80 Hz. The negative error in high frequencies is smaller on nonmasked cases and the masking increases it. The behaviour of the error of MDF value is similar to MNF value, but typically smaller in absolute value.

The line coefficients and the norm of residuals values not seems to be dependent on segment length. By comparing MSE values in Table 1 and norm of residual values in Tables 2-5, can be recognized that results are more or less correlated with each other.

Table 2: Line coefficients and the norm of the residuals of MNF values.

Codebook size 64 (6 bit)		
Segment length 16 samples		
Without mask	a=0.9611 b=5.0618	526.1498
Masking last 3	a=0.9479 b=5.6428	592.4270
Masking last 5	a=0.9401 b=6.1727	727.8094
Masking last 7	a=0.9425 b=5.9066	954.0903
Segment length 24 samples		
Without mask	a=0.9824 b=2.5583	280.5778
Masking last 4	a=0.9616 b=3.6733	486.0408
Masking last 8	a=0.9421 b=4.6243	833.8518
Masking last 12	a=0.9110 b=6.0588	1.1791e+003
Segment length 32 samples		
Without mask	a=0.9780 b=2.8869	301.1080
Masking last 5	a=0.9635 b=3.5139	394.1623
Masking last 10	a=0.9432 b=4.5146	626.5258
Masking last 15	a=0.9121 b=5.4824	972.4219

Table 3: Line coefficients and the norm of the residuals of MNF values.

Codebook size 256 (8 bit)		
Segment length 16 samples		
Without mask	a=0.9721 b=3.4008	412.3716
Masking last 3	a=0.9607 b=3.9323	544.9072
Masking last 5	a=0.9552 b=4.3098	711.5584
Masking last 7	a=0.9553 b=4.3155	946.9896
Segment length 24 samples		
Without mask	a=0.9865 b=1.7056	242.4786
Masking last 4	a=0.9660 b=2.8420	505.2355
Masking last 8	a=0.9469 b=3.8802	832.9791
Masking last 12	a=0.9160 b=5.3868	1.1716e+003
Segment length 32 samples		
Without mask	a=0.9752 b=2.8877	292.1546
Masking last 5	a=0.9605 b=3.5969	423.3512
Masking last 10	a=0.9412 b=4.5570	651.8788
Masking last 15	a=0.9119 b=5.4024	979.2064

Table 4: Line coefficients and the norm of the residuals of MDF values.

Codebook size 64 (6 bit)		
Segment length 16 samples		
Without mask	c=0.9943 d=0.9374	337.6673
Masking last 3	c=0.9895 d=1.0218	344.2408
Masking last 5	c=0.9837 d=1.1714	385.5636
Masking last 7	c=0.9689 d=1.4947	501.9240
Segment length 24 samples		
Without mask	c=0.9949 d=0.6864	291.5252
Masking last 4	c=0.9890 d=0.8036	355.9760
Masking last 8	c=0.9774 d=1.0882	477.4020
Masking last 12	c=0.9328 d=2.3365	708.1398
Segment length 32 samples		
Without mask	c=0.9960 d=0.6308	279.4163
Masking last 5	c=0.9910 d=0.7421	295.6508
Masking last 10	c=0.9807 d=1.0079	361.8950
Masking last 15	c=0.9445 d=1.9601	574.9671

Table 5: Line coefficients and the norm of the residuals of MDF values.

Codebook size 256 (8 bit)		
Segment length 16 samples		
Without mask	c=0.9955 d=0.5822	261.3096
Masking last 3	c=0.9914 d=0.6590	289.8141
Masking last 5	c=0.9863 d=0.7767	344.2559
Masking last 7	c=0.9717 d=1.1063	469.8654
Segment length 24 samples		
Without mask	c=0.9978 d=0.3327	243.8635
Masking last 4	c=0.9918 d=0.4807	296.6823
Masking last 8	c=0.9806 d=0.7793	422.6246
Masking last 12	c=0.9365 d=2.0190	672.4723
Segment length 32 samples		
Without mask	c=0.9932 d=0.7448	261.7802
Masking last 5	c=0.9884 d=0.8634	287.3707
Masking last 10	c=0.9779 d=1.1613	362.2217
Masking last 15	c=0.9426 d=2.0834	570.4948

3.2 Contemplation of Error

Examining the mean absolute error of MNF and MDF values frequency-by-frequency over clinically interesting frequency range from 40 Hz to 180 Hz is an entirely novel approach.

The mean absolute error (MAE) is calculated by sorting the value pairs (Equation 8) in increasing order and averaging the differences between original and processed value inside the pair. It must be noticed that the distribution of the value pairs is not uniform; on the contrary, the average value is in some cases coarse.

By examining Figures 2 – 4, it can be easily noticed that the mean absolute error of MNF and MDF get the least values between 80 and 120 Hz in all processing variations. Error is very moderate within this range, and the segment length itself doesn't dominate the error.

In the range less than 80 Hz, the error increases when more coefficients are masked out. However, behaviour is similar with MNF and MDF values and also with codebook size 64 (6 bit) and codebook size 256 (8 bit).

The most prominent differences can be seen in the range over 120 Hz. The error is multifold compared to other ranges and heavily increasing when more coefficients are masked out. At this range the errors are also more dependent on the codebook size.

Generally, the MNF error is larger than the MDF error. The segment lengths have not fundamental effect on error. Again, by comparing MSE values in Table 1 and peak level of the MAE in the range over 120 Hz in Figures 2-5, can be recognized that results are more or less correlated with each other, but not so evidently than in case of the norm of residual values.

4 CONCLUSIONS

The main value of this study was to reveal the complexity of error evaluation on EMG signal lossy compression studies. Guerrero and Mailhes (1997) have used standard deviation estimator -based SNR to evaluate the quality of the process. Wellig et al. (1998) have used both SNR and PRD on quality evaluation. Berger et al. (2003) use energy -based SNR as a tool for quality evaluation. None of these studies cover any medical parameters. Chan, Lovely and Hudgins (1997) were first ones to use medical parameters in performance evaluation. Carotti et al. (2006) have used both MSE and some medical parameters, including MNF and MDF, for quality evaluation. Examination is made via four force levels and the results show a valid correlation between MSE, MNF, and MDF values. Grönfors, Reinikainen and Sihvonen (2006) have used PRD value and percentual differences of MNF and MDF values in quality evaluation. Also these values indicate correlative behaviour. The use of averaged values over signals is common for all the referred studies.

The averaged processing errors with standard deviations of medical parameters form the baseline for the evaluation of a lossy compression method. However, there are pitfalls in the use of averaged error values. Only the error examinations over the whole clinically interesting range of parameter values expose the fidelity.

In this study we have used frequency-by-frequency aspect and compared synchronically generated medical parameters of original and processed signals. We have found that there is more or less correlation between MSE values and errors in medical parameters. However, this interdependency can only reveal the coarse amount of error, not errors natural for a specific range of MNF or MDF values.

The contemplation of error approach (chapter 3.2) has strong analytic use in finding out the values for which the medical parameters are valid. The parameter model approach (chapter 3.1) has both theoretical, analytical, value and practical, predictive usage. The generated regression line can be used for estimating the true value of the processed parameter. Together both approaches can produce a tool for calculating the corrected MNF and MDF value and an index for their quality.

Some of the achieved results are hypothetical, such as the best achived compression ratio has the worst MSE and the effect of masking on error in high frequency range. With DCT-based method, the segment length seems not to have prominent effect on error as with direct vector quantization based method has (Grönfors and Päivinen, 2006).The method should be further tested with larger datasets and with larger quantity of different lossy compression methods.

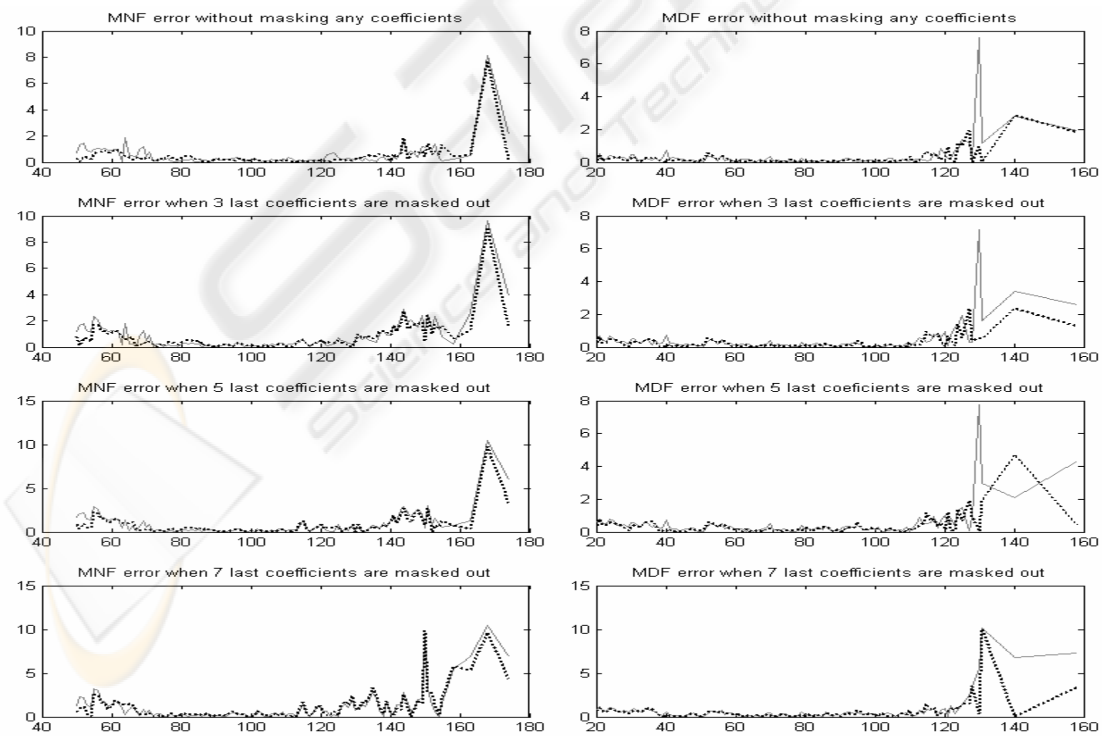

Figure 2: Mean absolute errors of MNF and MDF values for segment length 16. Solid line for codebook size 64 and dotted line for codebook size 256.

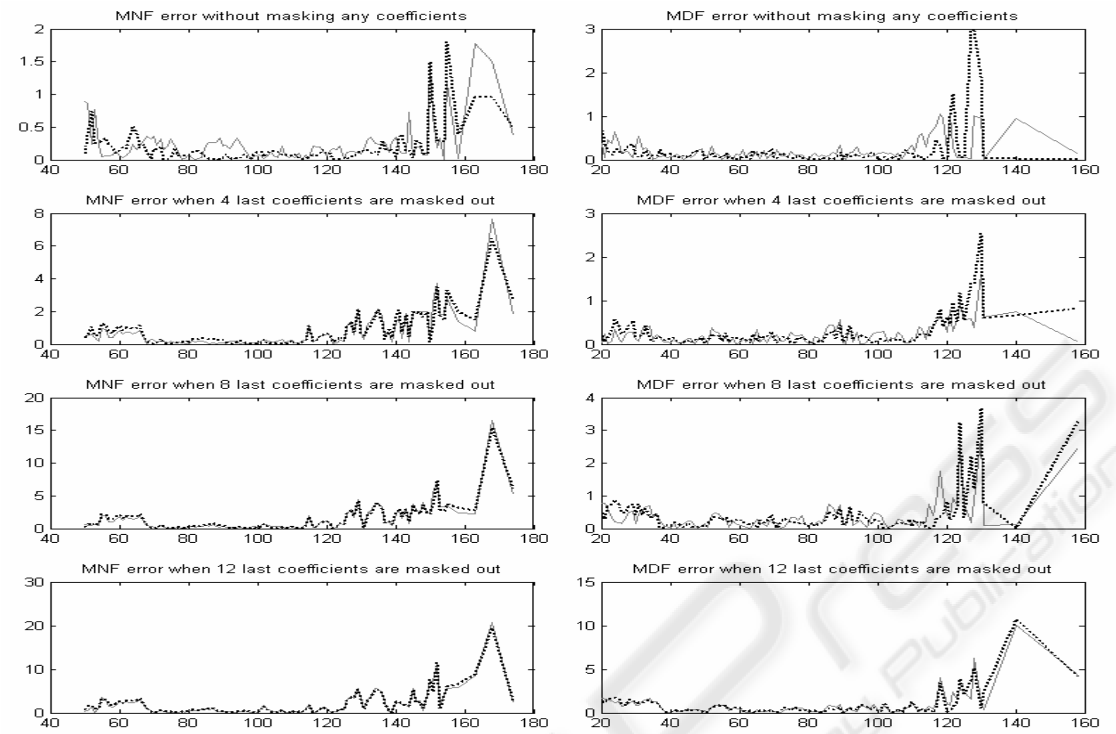

Figure 3: Mean absolute errors of MNF and MDF values for segment length 24. Solid line for codebook size 64 and dotted line for codebook size 256.

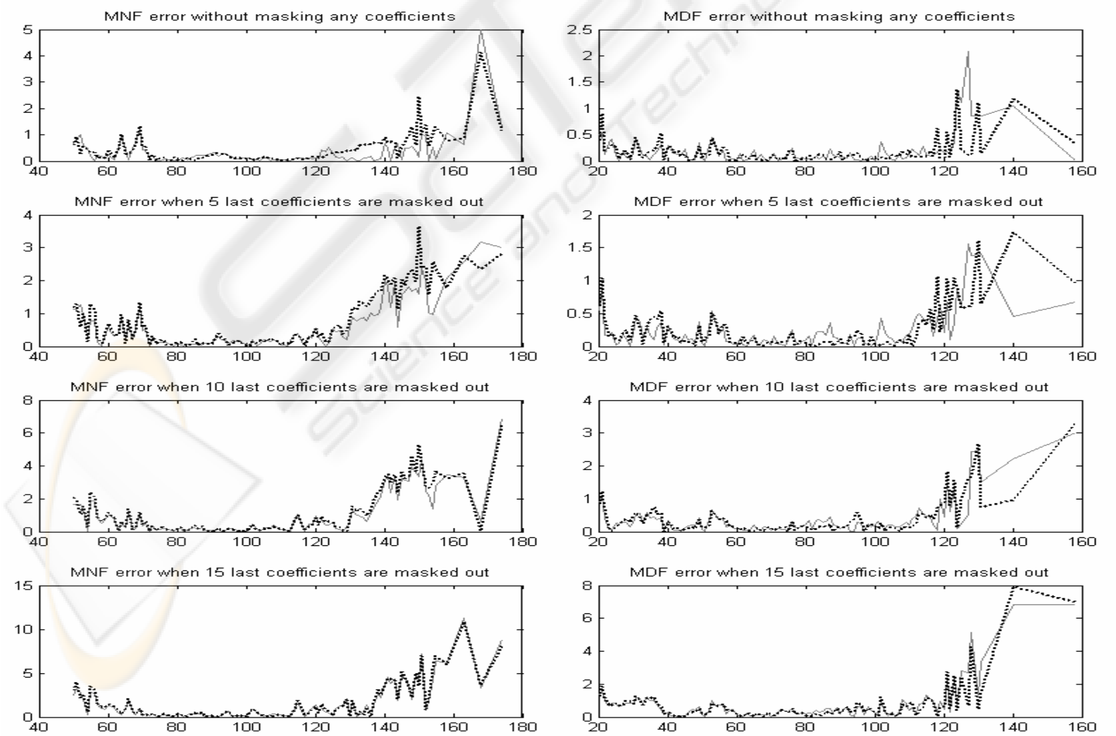

Figure 4: Mean absolute errors of MNF and MDF values for segment length 32. Solid line for codebook size 64 and dotted line for codebook size 256.

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