ENHANCED MODIFIED BARK SPECTRAL DISTORTION (EMBSD): AN OBJECTIVE SPEECH QUALITY MEASURE BASED ON AUDIBLE DISTORTION AND COGNITION MODEL

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ABSTRACT

An objective speech quality measure estimates speech quality of a test utterance without the involvement of human listeners. Recently, the performance of objective speech quality measures has been greatly improved by adopting auditory perception models derived from psychoacoustic studies. These measures estimate perceptual distortion of test speech by comparing it with the original speech in a perceptually relevant domain. These types of measures are called perceptual domain measures.

Recently, the Speech Processing Lab at Temple University developed a perceptual domain measure called the Modified Bark Spectral Distortion (MBSD). The MBSD measure extended the Bark Spectral Distortion (BSD) measure by incorporating noise masking threshold into the algorithm to differentiate audible and inaudible distortions. The performance of the MBSD is comparable to that of the International Telecommunication Union – Telecommunication standardization sector (ITU-T) Recommendation P.861 for speech data with various coding distortions. Since the MBSD uses psychoacoustic results derived using steady-state signals such as sinusoids, the performance of the MBSD has been examined by scaling the noise masking

threshold and omitting the spreading function in noise masking threshold calculation.

Based on experiments with Time Division Multiple Access (TDMA) data containing distortions encountered in real network applications, the performance of the MBSD has been further enhanced by modifying some procedures and adding a new cognition model. The Enhanced MBSD (EMBSD) shows significant improvement over the MBSD for TDMA data. Also, the performance of the EMBSD is better than that of the ITU-T Recommendation P.861 for TDMA data.

The performance of the EMBSD was compared to various other objective speech quality measures with the speech data including a wide range of distortion conditions. The EMBSD showed clear improvement over the MBSD and had the correlation coefficient of 0.89 for the conditions of MNRUs, codecs, tandem cases, bit errors, and frame erasures.

Objective speech quality measures are evaluated by comparing the objective estimates with the subjective test scores. The Mean Opinion Score (MOS) has been the usual subjective speech quality test used to evaluate objective speech quality measures because MOS is the most common subjective measure used to evaluate speech compression codecs. However, current objective speech quality measures estimate subjective scores by comparing the test speech to the original speech. This approach has more in common with the Degradation Mean Opinion Score (DMOS) test than with the MOS test. Recent

experiments performed at Nortel Networks in Ottawa also have indicated that the current objective speech quality measures are better correlated with the DMOS scores than with the MOS scores. So, it is more appropriate to evaluate current objective speech quality measures with DMOS scores.

The correlation between the objective estimates and the subjective scores has been used as a performance parameter for evaluation of objective speech quality measures. However, it is inappropriate to compare the correlation coefficients of an objective speech quality measure for different speech data because the correlation coefficient of an objective speech quality measure depends on the distribution of the subjective scores in the speech database. Accordingly, the Standard Error of the Estimates (SEE) is proposed as a performance parameter for evaluation of objective speech quality measures. The SEE is an unbiased statistic providing an estimate of the deviation from the regression line between two variables. The SEE has several advantages over the correlation coefficient as a performance parameter for examining the performance of objective measures.

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CHAPTER 1

INTRODUCTION

Today's telecommunications and computer networks are eventually going to converge into a common broadband network system in which efficient integration of voice, video, and data services will be required. As the data network becomes ubiquitous, the integration of voice and data services over the data network will benefit users as well as service providers. Digital representation of voice and video signals makes a common broadband network system possible. In this environment, it is highly desirable that speech be coded very efficiently to share limited network resources such as bandwidth in an efficient way. Typically, efficient digital representation of speech results in reduced quality of the decoded speech. The main goal of speech coding research is to simultaneously reduce the bit rate and complexity, and maintain the original speech quality [Jayant and Noll, 1984]. Among the performance parameters for development of speech coders, bit rate and complexity can be directly calculated from the coding algorithm itself, but a measurement of speech quality is usually performed by human listeners. Such listening tests are expensive, time-consuming, and difficult to administer. In addition, such tests seldom provide much insights into the factors which may lead to improvements in the evaluated systems [Quackenbusch et al., 1988].

As voice communication systems have been rapidly changing, there is increasing interest in the development of a robust objective speech quality measure that correlates well with subjective speech quality measures. Although objective speech quality measures are not expected to completely replace subjective speech quality measures, a good objective speech quality measure would be a valuable assessment tool for speech codec development and for validation of communication systems using speech codecs. An objective speech quality measure could be used to improve speech quality in such systems as Analysis-By-Synthesis (ABS) speech coders [Sen and Holmes, 1994]. Objective speech quality measures may eventually have a role to play in the selection of speech codecs for certain applications.

An ideal objective speech quality measure should be able to assess the quality of distorted speech by simply observing a small portion of the speech in question, with no access to the original (or reference) speech [Quackenbusch et al., 1988]. An attempt to implement such a measure was the Output-Based Quality (OBQ) measure [Jin and Kubicheck, 1996]. Since the OBQ examines only the output speech to measure the distortion, it needs to construct an internal reference database capable of covering a wide range of human speech variations. It is a particularly challenging problem to construct such a complete reference database. The performance of the OBQ was unreliable both for vocoders and for various adverse conditions such as channel noise and Gaussian noise [Jin and

Kubicheck, 1996]. Consequently, current objective speech quality measures base their estimates on using both the original and distorted speech, as shown in Figure 1.

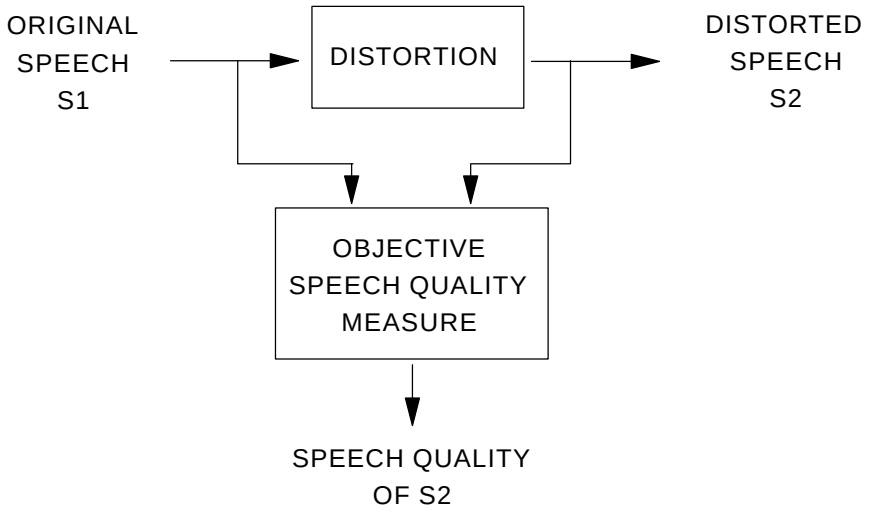


Figure 1. Current Objective Speech Quality Measures Based on Both Original and Distorted Speech.

A voice processing system can be regarded as a distortion module, as shown in Figure 1. Distortion could be caused by speech codecs, background noise, channel impairments such as bit errors and frame erasures, echoes, and delays. Voice processing systems are assumed to degrade the quality of the original

speech in the current objective speech quality measures. However, it has been shown that the output speech of a voice processing system sometimes sounds better than the input speech with background noise for some processes (e.g. Enhanced Variable Rate Codec (EVRC)). The current objective speech quality measures do not take into consideration such situations.

Over the years, numerous objective speech quality measures have been proposed and used for the evaluation of speech coding devices as well as communication systems. These measures can be classified according to the domain in which they estimate the distortion: time domain, spectral domain, and perceptual domain. Time domain measures are usually applicable to analog or waveform coding systems in which the goal is to reproduce the waveform. Signal-to-Noise Ratio (SNR) and Segmental SNR (SNRseg) are typical time domain measures. Spectral domain measures are more reliable than time-domain measures and less sensitive to the occurrence of time misalignments between the original and the distorted speech. These measures have been thoroughly reviewed and evaluated in [Quackenbusch et al., 1988]. Most spectral domain measures are closely related to speech codec design, and use the parameters of speech production models. Their performance is limited both by the constraints of the speech production models used in codecs and by the failure of speech production models to adequately describe the listeners' auditory response.

Recently, researchers in the development of objective speech quality measures have begun to base their techniques on psychoacoustic models. Such measures are referred to as perceptual domain measures. Based as they are on models of human auditory perception, perceptual domain measures would appear to have the best chance of predicting subjective quality of speech. These measures transform the speech signal into a perceptually relevant domain incorporating human auditory models. Several perceptual domain measures are reviewed and their strengths and weakness are discussed.

The Speech Processing Lab at Temple University developed a perceptual domain measure, the Modified Bark Spectral Distortion (MBSD) measure [Yang et al., 1997]. The MBSD is a modification of the Bark Spectral Distortion (BSD) measure [Wang et al., 1992]. Noise masking threshold has been incorporated into the MBSD to differentiate audible and inaudible distortions. The performance of the MBSD was comparable to the ITU-T Recommendation P.861 for speech data with coding distortions [Yang et al., 1998] [Yang and Yantorno, 1998]. The noise masking threshold calculation is based on the results of psychoacoustic experiments using steady-state signals such as single tones and narrow band noise rather than speech signals. It may not be appropriate to use this noise masking threshold for non-stationary speech signals; therefore, the performance of the MBSD has been studied by scaling the noise masking threshold. The

MBSD has been improved by scaling the noise masking threshold by the factor of 0.7 for speech data with coding distortions [Yang and Yantorno, 1999].

Speech coding is only one area where distortions of the speech signal can occur. There are presently other situations where distortions of the speech signal can take place, e.g., cellular phone systems, and in this environment there can be more than one type of distortion. Also, there are other distortions encountered in real network applications such as codec tandeming, bit errors, frame erasures, and variable delays. Recently, the performance of the MBSD has been examined with Time Division Multiple Access (TDMA) speech data generated by AT&T. The data was collected in real network environments, and have given valuable insights into how the MBSD may be improved. Based on the results of these experiments, the MBSD has been further improved, resulting in the development of the Enhanced MBSD (EMBSD). The performance of the EMBSD is better than that of the ITU-T Recommendation P.861 for TDMA speech data.

Objective speech quality measures are evaluated by comparing the objective estimates with the subjective test scores. The Mean Opinion Score (MOS) has been the usual subjective speech quality test used to evaluate objective speech quality measures. In a MOS test, listeners are not provided with an original speech sample and rate the overall speech quality of the distorted speech sample. However, objective speech quality measures estimate subjective scores by comparing the distorted speech to the original speech, which has more

in common with a Degradation Mean Opinion Score (DMOS) test in which listeners listen to an original speech sample before each distorted speech sample. An evaluation was performed using MOS difference data (MOS of original speech – MOS of distorted speech) because no DMOS data were available [Yang et al., 1998] [Yang and Yantorno, 1999]. The objective speech quality measures showed better correlation with MOS difference than with MOS. More recently, current perceptual objective speech quality measures were evaluated with both MOS and DMOS at Nortel Networks in Ottawa [Thorpe and Yang, 1999]. These results show that current objective speech quality measures are better correlated with DMOS scores than with MOS scores.

The Pearson product-moment correlation coefficient has been used as a performance parameter for evaluation of objective speech quality measures. However, the correlation coefficient has some shortcomings that can be helped by considering some additional measures of performance. For instance, comparing performance with the different groups of conditions is difficult because the groups have different types of distortions, different value ranges, and small number of data points. Also, the correlation coefficient is highly sensitive to outliers. For the same reasons, it would be inappropriate to compare the correlation coefficients of an objective speech quality measure for different speech database.

So, the Standard Error of the Estimates (SEE) has been proposed as a new performance estimator for evaluation of objective speech quality measures. The SEE is an unbiased statistic for the estimate of the deviation from the best-fitting curve between the objective estimates and the actual subjective scores. The SEE has several advantages over the correlation coefficient as a performance parameter. It is independent of the distribution of the subjective scores of a speech data, so it is possible to compare the SEE with one data set to that of another data set. This would be also very useful when analyzing the performance over a certain distortion condition. The SEE also provides the performance of an objective speech quality measure in terms of confidence interval of objective estimates. This information could be very useful to users who want to understand the capability of an objective speech quality measure to predict subjective scores.

Chapter 2 introduces various objective speech quality measures and discusses their strengths and weakness. Chapter 3 deals with evaluation of objective speech quality measures. Conventional evaluation of objective speech quality measures has been analyzed and a new evaluation scheme with DMOS and the SEE has been proposed. The MBSD measure is described in Chapter 4 and several experiments of the MBSD for improvement with TDMA data are discussed in Chapter 5. The EMBSD measure is presented in Chapter 6 and its performance with three different speech data sets is analyzed and compared to

other perceptual objective speech quality measures in Chapter 7. Future research in this exciting field is discussed in Chapter 8.

CHAPTER 2

BACKGROUND

The goal of any objective speech quality measure is to predict the scores of a subjective speech quality measure representing listeners' responses to the distorted speech. Two subjective speech quality measures frequently used in telecommunications systems are introduced in this chapter. Various objective speech quality measures are then reviewed according to the domain in which they estimate the distortion. Both advantages and disadvantages of each objective quality measure are discussed.

2.1. Subjective Speech Quality Measures

Speech quality measures based on ratings by human listeners are called subjective speech quality measures. These measures play an important role in the development of objective speech quality measures because the performance of objective speech quality measures is generally evaluated by their ability to predict some subjective quality assessment. Human listeners listen to speech and rate the speech quality according to the categories defined in a subjective test. The procedure is simple but it usually requires a great amount of time and cost.

These subjective quality measures are based on the assumption that most listeners' auditory responses are similar so that a reasonable number of listeners can represent all human listeners. To perform a subjective quality test, human subjects (listeners) must be recruited, and speech samples must be determined depending on the purpose of the experiments. After collecting the responses from the subjects, statistical analysis is performed for the final results. A comprehensive review of subjective quality measures is available in the literature [Quackenbush et al., 1988]. Two subjective speech quality measures used frequently to estimate performance for telecommunication systems are the Mean Opinion Score (MOS, also known as absolute category rating) [Voiers, 1976], and Degradation Mean Opinion Score (DMOS, also known as degradation category rating) [Thorpe and Shelton, 1993] [Dimolitsas et al., 1995].

2.1.1. Mean Opinion Score (MOS)

MOS is the most widely used method in the speech coding community to estimate speech quality. This method uses an Absolute Category Rating (ACR) procedure. Subjects (listeners) are asked to rate the overall quality of a speech utterance being tested without being able to listen to the original reference, using

the following five categories as shown in Table 1. The MOS score of a speech sample is simply the mean of the scores collected from listeners.

Table 1. MOS and Corresponding Speech Quality

Rating	Speech Quality
5	Excellent
4	Good
3	Fair
2	Poor
1	Bad

An advantage of the MOS test is that listeners are free to assign their own perceptual impression to the speech quality. At the same time, this freedom poses a serious disadvantage because individual listeners' "goodness" scales may vary greatly [Voiers, 1976]. This variation can result in a bias in a listener's judgments. This bias could be avoided by using a large number of listeners. So, at least 40 subjects are recommended in order to obtain reliable MOS scores [ITU-T Recommendation P.800, 1996].

2.1.2. Degradation Mean Opinion Score (DMOS)

In the DMOS, listeners are asked to rate annoyance or degradation level by comparing the speech utterance being tested to the original (reference). So, it is classified as the Degradation Category Rating (DCR) method. The DMOS provides greater sensitivity than the MOS, in evaluating speech quality, because the reference speech is provided. Since the degradation level may depend on the amount of distortion as well as distortion type, it would be difficult to compare different types of distortions in the DMOS test. Table 2 describes the five DMOS scores and their corresponding degradation levels.

Table 2. DMOS and Corresponding Degradation Levels

Rating	Degradation Level
5	Inaudible
4	Audible but not annoying
3	Slightly annoying
2	Annoying
1	Very annoying

Thorpe and Shelton (1993) compared the MOS with the DMOS in estimating the performance of eight codecs with dynamic background noise [Thorpe and Shelton, 1993]. According to their results, the DMOS technique can

be a good choice where the MOS scores show a floor (or ceiling) effect compressing the range. However, the DMOS scores may not provide an estimate of the absolute acceptability of the voice quality for the user.

2.2. Objective Speech Quality Measures

An ideal objective speech quality measure would be able to assess the quality of distorted or degraded speech by simply observing a small portion of the speech in question, with no access to the original speech [Quackenbush et al., 1988]. One attempt to implement such an objective speech quality measure was the Output-Based Quality (OBQ) measure [Jin and Kubicheck, 1996]. To arrive at an estimate of the distortion using the output speech alone, the OBQ needs to construct an internal reference database capable of covering a wide range of human speech variations. It is a particularly challenging problem to construct such a complete reference database. The performance of OBQ was unreliable both for vocoders and for various adverse conditions such as channel noise and Gaussian noise.

Current objective speech quality measures base their estimates on both the original and the distorted speech even though the primary goal of these

measures is to estimate MOS test scores where the original speech is not provided.

Although there are various types of objective speech quality measures, they all share a basic structure composed of two components as shown in Figure 2.

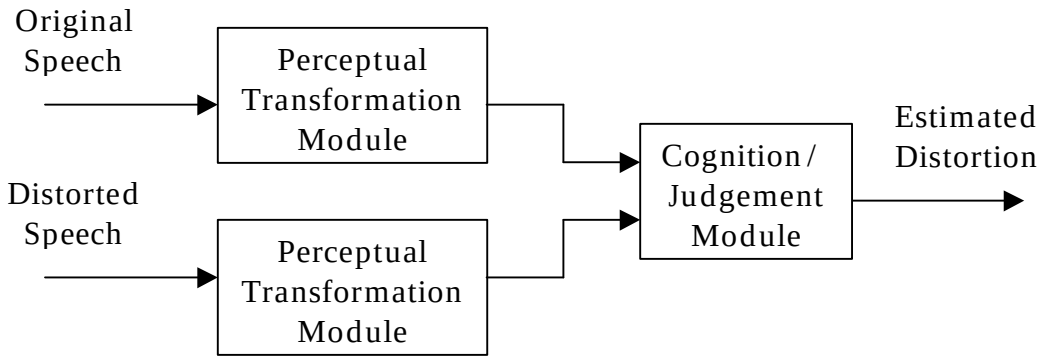


Figure 2. Basic Structure of Objective Speech Quality Measures.

The first component is called the perceptual transformation module. In this module, the speech signal is transformed into a perceptually relevant domain such as temporal, spectral, or loudness domain. The choice of domain differs from measure to measure. Current objective measures use psychoacoustic models, and their performance has been greatly improved compared to the

previous measures that did not incorporate psychoacoustic responses. The second component is called the cognition/judgement module. This module models listeners' cognition and judgment of speech quality in the subjective test. After the original and the distorted speech are converted into a perceptually relevant domain, through the perceptual transformation module, the cognition/judgment module compares the two perceptually transformed signals in order to generate an estimated distortion. Some measures use a simple cognition/judgment module like average Euclidean distance while others use a complex one such as an artificial neural network or fuzzy logic. Recently, researchers in this field have been focusing on this module because they realize that a simple distance metric cannot cover the wide range of distortions encountered in modern voice communication systems. The potential benefits of including this module are not yet fully understood.

Objective speech quality measures can be classified according to the perceptual domain transformation module being used, and these are: time domain measures, spectral domain measures, and perceptual domain measures. In the following sections, these classes of measures are briefly reviewed.

2.2.1. Time Domain Measures

Time domain measures are usually applicable to analog or waveform coding systems in which the goal is to reproduce the waveform itself. Signal-to-noise ratio (SNR) and segmental SNR (SNRseg) are well known time domain measures [Quackenbush et al., 1988]. Since speech waveforms are directly compared in time domain measures, synchronization of the original and distorted speech is extremely important. If the waveforms are not synchronized, the results of these measures will have little to do with the distortions introduced by the speech processing system. Since current sophisticated codecs are designed to generate the same sound of the original speech using speech production models rather than simply reproducing the original speech waveform, these time domain measures cannot be used in those applications.

2.2.1.1. Signal-to-Noise Ratio (SNR)

This measure is only appropriate for measuring the distortion of the waveform coders that reproduce the input waveform. The SNR is very sensitive to the time alignment of the original and distorted speech. If not synchronized,

the SNR does not reflect the amount of the degradation of the distorted speech. The SNR is measured as

$$SNR = 10\log_{10}\frac{\sum_{i=1}^{N} x^2(i)}{\sum_{i=1}^{N}\left(x(i)-y(i)\right)^2} \qquad (1)$$

where *x(i)* is the original speech signal, *y(i)* is the distorted speech reproduced by a speech processing system, *i* is the sample index, and *N* is the total number of samples in both speech signals.

This measure gives some indication of quality of stationary, non-adaptive systems but is obviously not adequate for other types of distortions. It has been demonstrated [McDermott, 1969] [McDermott et al., 1978] [Tribolet et al., 1978] that the SNR is a poor estimator of subjective speech quality for a broad range of speech distortions and therefore is of little interest as a general objective speech quality measure.

2.2.1.2. Segmental Signal-to-Noise Ratio (SNRseg)

The most popular class of the time-domain measures is the segmental signal-to-noise ratio (SNRseg). SNRseg is defined as an average of the SNR values of short segments. The performance of SNRseg is a good estimator of speech quality for waveform coders [Noll, 1974] [Barnwell and Voiers, 1979], but its performance is poor for vocoders where the goal is to generate the same speech sound rather than to produce the speech waveform itself. SNRseg can be formulated as

$$SNRseg = \frac{10}{M}\sum_{m=0}^{M-1}\log_{10}\sum_{i=Nm}^{Nm+N-1}\left(\frac{x^2(i)}{\left(x(i)-y(i)\right)^2}\right) \qquad (2)$$

where *x(i)* is the original speech signal, *y(i)* is the distorted speech reproduced by a speech processing system, *N* is the segment length and *M* is the number of segments in the speech signal. The length of segments is typically 15 to 20 ms.

The above definition of SNRseg poses a problem if there are intervals of silence in the speech utterance. In segments in which the original speech is nearly zero, any amount of noise can give rise to a large negative signal-to-noise ratio for that segment, which could appreciably bias the overall measure of SNRseg.

This problem is resolved by including the SNR of the frame only if the frame's energy is above a specified threshold [Quackenbusch et al., 1988].

Even though SNRseg is a poor estimator of subjective speech quality for vocoders, it is still the most widely used objective quality measure for vocoders [Voran and Sholl, 1995].

2.2.2. Spectral Domain Measures

Several spectral domain measures have been proposed in the literature including the log likelihood ratio measures [Itakura, 1975] [Crochiere et al., 1980] [Juang, 1984], the Linear Predictive Coding (LPC) parameter distance measures [Barnwell et al., 1978] [Barnwell and Voiers, 1979], the cepstral distance measures [Gray and Markel, 1976] [Tohkura, 1987] [Kitawaki et al., 1988], and the weighted slope spectral distance measure [Klatt, 1976] [Klatt, 1982]. These distortion measures are generally computed using speech segments typically between 15 and 30 ms long. They are much more reliable than the time-domain measures and less sensitive to the occurrence of time misalignments between the original and the coded speech [Quackenbush et al., 1988]. However, most spectral domain measures are closely related to speech codec design and use the parameters of speech production models. Their ability to adequately describe the

listeners' auditory response is limited by the constraints of the speech production models.

2.2.2.1. Log Likelihood Ratio (LLR) Measures

The LLR is referred to as the Itakura distance measure. The LLR distance for a speech segment is based on the assumption that a speech segment can be represented by a *p*-th order all-pole linear predictive coding (LPC) model of the form

$$x[n] = \sum_{m=1}^{p} a_m x[n-m] + G_x u[n] \qquad (3)$$

where *x[n]* is the *n*-th speech sample, a_m (for $m = 1, 2, \ldots, p$) are the coefficients of an all-pole filter, G_x is the gain of the filter and *u[n]* is an appropriate excitation source for the filter. The speech waveform is windowed to form frames 15 to 30 ms in length. The LLR measure then is defined as

$$LLR = \log\left(\frac{\vec{a}_x \overline{R}_y \vec{a}_x^T}{\vec{a}_y \overline{R}_y \vec{a}_y^T}\right) \qquad (4)$$

where $\vec{a}_x$ is the LPC coefficient vector (1, $-a_x(1)$, $-a_x(2)$, . . ., $-a_x(p)$) for the original speech $x[n]$, $\vec{a}_y$ is the LPC coefficient vector (1, $-a_y(1)$, $-a_y(2)$, . . ., $-a_y(p)$) for the distorted speech $y[n]$, and $\overline{R}_y$ is the autocorrelation matrix for the distorted speech.

Since the LLR is based on the assumption that the speech signals are well represented using an all-pole model, the performance of the LLR is limited by the distortion conditions where this assumption is valid [Crochiere et al., 1980]. This assumption may not be valid if the original speech is passed through a voice communication system that significantly changes the statistics of the original speech.

2.2.2.2. LPC Parameter Measures

Motivated by linear prediction of speech [Markel and Gray, 1976], objective speech quality measures can compare the parameters of the linear prediction vocal tract models of the original and distorted speech. The parameters used in LPC parameter measures can be the prediction coefficients, or transformations of the predictor coefficients such as area ratio coefficients.

Linear prediction analysis is performed over 15 to 30 ms frames to obtain LPC parameters which are used for the computation of distortion.

Barnwell et al. (1978) have proposed parameter distance measures of the form

$$d(Q,p,m)=\left(\frac{1}{N}\sum_{i=1}^{N}\left|Q(i,m,x)-Q(i,m,y)\right|^{p}\right)^{1/p} \qquad (5)$$

where *d(Q,p,m)* is the distance measure of the analysis frame *m*, *p* is the power in the norm, and *N* is the order of the LPC analysis [Barnwell et al., 1978] [Barnwell and Voiers, 1979]. *Q(i,m,x)* and *Q(i,m,y)* are the *i-th* parameters of the corresponding frames of the original and distorted speech, respectively. The distance measure for each frame is summed for all frames as follows:

$$D(p)=\frac{\sum_{m=1}^{M}W(m)d(Q,p,m)}{\sum_{m=1}^{M}W(m)} \qquad (6)$$

where *D(p)* is the resultant estimated distortion, *M* is the total number of frames, and *W(m)* is a weight associated with the distance measure for the *m-th* frame. The weighting could, for example, be the energy in the reference analysis frame.

Barnwell et al. (1978) have investigated this measure with various forms of LPC parameters [Barnwell et al., 1978]. Among them, the log area ratio measure has been reported to have the highest correlation with subjective quality. Eq. (6) is a general formula that other objective speech quality measures can use in the calculation of a distortion value for a test sample.

2.2.2.3. Cepsrtal Distance (CD) Measures

The cepstral distance (CD) is another form of LPC parameter measure, because linear prediction coefficients also can be used to compute cepstral coefficients of the overall difference between an original and a corresponding coded speech cepstrum. The cepstrum computed from the LPC coefficients, unlike that computed directly from the speech waveform, results in an estimate of the smoothed speech spectrum [Kitawaki et al., 1988]. This can be written as

$$\log\left(\frac{1}{A(z)}\right) = \sum_{k=1}^{\infty} c(k) z^{-k} \qquad (7)$$

where *A(z)* is the LPC analysis filter polynomial, *c(k)* denotes the *k-th* cepstral coefficient, and *z* can be set equal to e^{-jw}. Also, there is another way to calculate

the cepstral coefficients from the linear predictor coefficients [Markel and Gray, 1976]:

$$nc(n) - na(n) = \sum_{k=1}^{n-1} (n-k)c(n-k)a(k) \quad \text{for } n = 1, 2, 3, \ldots \quad (8)$$

where $a(0) = 1$ and $a(k) = 0$ for $k > p$. In this expression, the $a(k)$ is the linear predictor coefficients and p is the order of the linear predictor. The cepstral coefficients are computed recursively from Eq. (8).

An objective speech quality measure based on the cepstral coefficients computes the distortion of a frame [Gray and Markel, 1976] [Kitawaki et al., 1982]:

$$d(c_x, c_y, 2, m) = \left[\left[c_x(0) - c_y(0) \right]^2 + 2 \sum_{k=1}^{L} \left[c_x(k) - c_y(k) \right]^2 \right]^{1/2} \quad (9)$$

where d is the L_2 distance for frame m and $c_x(k)$ and $c_y(k)$ are the cepstral coefficients for the original and distorted speech, respectively. The final distortion is calculated over all frames using Eq. (6).

2.2.2.4. Weighted Slope Spectral Distance Measure

A speech spectrum can be analyzed using a filter bank. Klatt (1976) uses thirty-six overlapping filters of progressively larger bandwidths to estimate the smoothed short-time speech spectrum every 12 ms [Klatt, 1976]. The filter bandwidths approximate critical bands in order to give equal perceptual weight to each band [Zwicker, 1961]. Rather than using the absolute spectral distance per band to estimate distortion, Klatt (1982) uses a weighted difference between the spectral slopes in each band [Klatt, 1982]. This method assumes that spectral variation plays an important role in human perception of speech quality.

In this measure, the spectral slope is first computed in each critical band as follows:

$$\begin{aligned} S_x(k) &= V_x(k+1) - V_x(k) \\ S_y(k) &= V_y(k+1) - V_y(k) \end{aligned} \qquad (10)$$

where $V_x(k)$ and $V_y(k)$ are the original and distorted spectra in decibels, $S_x(k)$ and $S_y(k)$ are the first order slopes of these spectra and k is the critical band index. Next, a weight for each band is calculated based on the magnitude of the spectrum in that band. Klatt computes the weight using a global spectral maximum as well as a local spectral maximum. The weight is larger for those

bands whose spectral magnitude is closer to the global or local spectral maxima. The spectral distortion is computed for a frame as

$$d(m) = K_{spl}\left(K_x - K_y\right) + \sum_{k=1}^{36} W(k)\left[S_x(k) - S_y(k)\right]^2 \qquad (11)$$

where K_x and K_y are related to the overall sound pressure level of the original and distorted speech and K_{spl} is a parameter that can be varied. The overall distortion is obtained by averaging the spectral distortion over all frames in an utterance.

2.2.3. Psychoacoustic Results

Since current objective speech quality measures are based on psychoacoustic results, this section reviews those psychoacoustic results frequently used in current objective quality measures. Psychoacoustics is the study of the quantitative correlation of acoustical stimuli and human hearing sensations. Zwicker and Fastl (1990) have summarized the extensive results of psychoacoustic facts and models based on experimental data [Zwicker and Fastl, 1990]. The important psychoacoustic results used in objective speech quality

measures are: frequency selectivity, nonlinear response of human hearing system, masking effects, critical band concept, and loudness.

2.2.3.1. Critical Bands

The critical-band concept is important for describing hearing sensations. It was used in so many models and hypotheses that a unit was defined, leading to the so-called critical-band rate scale. This scale is based on the fact that our hearing system analyses a broad spectrum into parts that correspond to critical bands. It is well known that the inner ear performs the very important task of frequency separation; energy from different frequencies is transferred to and concentrated at different places along the basilar membrane. So, the inner ear can be regarded as a system composed of a series of band-pass filters each with an asymmetrical shape of frequency response. The center frequencies of these band-pass filters are closely related to the critical band rates.

Table 3 shows critical band rate, lower and upper limit of the critical bands [Zwicker and Fastl, 1990]. The critical bandwidth remains approximately 100 Hz up to a center frequency of 500 Hz, and a relative bandwidth of 20% for center frequencies above 500 Hz.

Critical-band rate has the unit “Bark” in memory of Barkhausen, a scientist who introduced the “phon”, a value describing loudness level for which the critical band plays an important role. The relationship between critical-band rate, *z*, and frequency, *f*, is important for understanding many characteristics of the human ear.

Table 3. Critical-Band Rate and Critical Bandwidths Over Auditory Frequency Range. Critical-Band Rate, *z*, Lower(f_l) and Upper(f_u) Frequency Limit of Critical Bandwidths, Δf_G, Centered at f_c

z (Bark)	$f_{l,} f_u$ (Hz)	f_c (Hz)	Δf_G (Hz)
0	0	50	100
1	100	150	100
2	200	250	100
3	300	350	100
4	400	450	110
5	510	570	120
6	630	700	140
7	770	840	150
8	920	1000	160
9	1080	1170	190
10	1270	1370	210
11	1480	1600	240
12	1720	1850	280
13	2000	2150	320
14	2320	2500	380
15	2700	2900	450
16	3150	3400	550
17	3700	4000	700
18	4400	4800	900
19	5300		

In many cases an analytic expression is useful to describe the dependence of critical-band rate and of critical bandwidth over the whole auditory frequency range [Zwicker, 1961]. The following two expressions have proven useful:

$$z = 13\arctan(0.76f) + 3.5\arctan(f/7.5)^2 \quad (12)$$

$$\Delta f_G = 25 + 75\left[1 + 1.4f^2\right]^{0.69} \quad (13)$$

where z is the critical band rate, f is the frequency in kHz, and Δf_G is the critical bandwidth in Hz.

2.2.3.2. Masking Effects

Auditory masking is the occlusion of one sound by another loud sound. This may happen if the sounds are simultaneous, or a loud sound can obliterate a sound closely following, or preceding it. Masking effects are differentiated according to temporal regions of masking relative to the presentation of the masker stimulus. Premasking takes place during the period of time before the masker is presented. Premasking plays a relatively secondary role, because the effect lasts only 20 ms, and therefore is usually ignored. Postmasking occurs

during the time the masker is not present. The effects of postmasking correspond to a decay of the effect of the masker. Postmasking lasts longer than 100 ms and ends after about a 200 ms delay. Both premasking and postmasking are referred to as non-simultaneous masking. On the other hand, simultaneous masking occurs when the masker and test sound are presented simultaneously.

To measure these effects quantitatively, the masked threshold is usually determined. The masked threshold is the sound pressure level of a test sound (usually a sinusoidal test tone), necessary to be just audible in the presence of a masker. Masked threshold, in all but a very few special cases, always lies above the absolute hearing threshold; it is identical to the absolute hearing threshold when the frequencies of the masker and the test sound are very different. The masked threshold depends on both the sound pressure level of the masker as well as the duration of the test sound. The dependence of masking effects on duration shows that the masked threshold of a test tone for duration of 200 ms is equal to that of long lasting sounds. For duration shorter than 200 ms, the masked threshold increases at a rate of 10 dB per decade as the duration decreases. This behavior can be ascribed to the temporal integration of the hearing system [Zwicker and Fastl, 1990].

Among the experiments on auditory masking, the threshold of pure tones masked by critical-band wide noise is interesting. Figure 3 shows this masked threshold at center frequencies of 0.25, 1, and 4 kHz. The level of each masking

noise is 60 dB and the corresponding bandwidths of the noises are 100, 160, and 700 Hz, respectively. Note that the slopes of the noises above and below the center frequency of each filter are very steep. The frequency dependence of the threshold masked by the 250 Hz narrow band noise seems to be broader. Also, the maximum of the masking threshold shows the tendency to be lower for higher center frequencies of the masker, although the level of the narrow-band masker is 60 dB at all center frequencies.

Figure 3. Level of Test Tone Just Masked by Critical-Band Wide Noise With Level of 60 dB, and Center Frequencies of 0.25, 1, and 4 kHz. The Broken Curve is the Threshold in Silence [Zwicker and Fastl, 1990].

2.2.3.3. Equal-Loudness Contours

Loudness belongs to the category of intensity sensations. Loudness is the sensation that corresponds most closely to the sound intensity of the stimulus. Loudness can be measured by answering the question of how much louder (or softer) a sound is heard relative to a standard sound. In psychoacoustics, the 1 kHz tone is the most common standard sound. The level of 40 dB of a 1 kHz tone is supposed to give the reference for loudness sensation, i.e. 1 sone. For loudness evaluations, the subject searches for the level increment that leads to a sensation that is twice as loud as that of the starting level. The average of many measurements of this kind indicates that the level of the 1 kHz tone in a plane field has to increase by 10 dB in order to enlarge the sensation of loudness by a factor of two. So, the sound pressure level of 40 dB of the 1 kHz tone has to be increased to 50 dB in order to double the loudness, which corresponds to 2 sones.

In addition to loudness, loudness level is also important. The loudness level is not only a sensation value but belongs somewhere between sensation and a physical value. It was introduced in the twenties by Barkhausen to characterize the loudness sensation of any sound with physical values. The loudness level of a sound is the sound pressure level of a 1 kHz tone in a plane wave that is as loud as the sound. The unit of loudness level is “phon”. Using the above definition, the loudness level can be measured for any sound, but best known are the

loudness levels for different frequencies of pure tones. A set of lines which connect points of equal loudness in the hearing area are called equal-loudness contours. Equal-loudness contours for pure tones are shown in Figure 4.

Figure 4. Equal-Loudness Contours for Pure Tones in a Free Sound Field. The Parameter is Expressed in Loudness Level, L_N and Loudness, N [Zwicker and Fastl, 1990].

The sound pressure level of 40 dB at 1 kHz tone corresponds to 40 phons as well as to 1 sone. The threshold in silence, where the limit of loudness sensation is reached, is also an equal-loudness contour, shown with a dashed line. The equal-loudness contours are almost parallel to the threshold in silence. However, at low frequencies, equal-loudness contours become shallower with high levels. The most sensitive area of threshold in silence is the frequency range between 2 and 5 kHz corresponding to a dip in all equal-loudness contours. As shown in Figure 4, loudness depends on the sound intensity as well as the frequency of a tone.

The relationship between loudness level and loudness sensation is formulated as follows [Bladon, 1981]:

$$S = 2^{(P-40)/10} \qquad \text{if } P > 40 \qquad (14.1)$$

$$S = \left(P/40\right)^{2.642} \qquad \text{if } P < 40 \qquad (14.2)$$

where P is the loudness level in phon and S is the loudness in sone.

2.2.4. Perceptual Domain Measures

Most spectral domain measures are closely related to speech codec design, and use the parameters of speech production models. Their performance is limited by the constraints of the speech production models used in codecs. In contrast to the spectral domain measures, perceptual domain measures are based on models of human auditory perception. These measures transform speech signal into a perceptually relevant domain such as bark spectrum or loudness domain, and incorporate human auditory models. Perceptual domain measures appear to have the best chance of predicting subjective quality of speech. Recently, researchers in this field have begun to consider that the cognition/judgement model plays an important role in estimating subjective quality. However, since most of current cognition models are based on the optimization with one type of speech data, the performance of those measures may not function properly with different speech data. Also, these measures would have the risk of not describing perceptually important effects relevant to speech quality but simply curve-fitting by parameter optimization [Hauenstein, 1998].

2.2.4.1. Bark Spectral Distortion (BSD)

BSD was developed at the University of California, Santa Barbara [Wang et al., 1992]. It was essentially the first objective measure to incorporate psychoacoustic responses. Its performance was quite good for speech coding distortions as compared to traditional objective measures such as time domain measures and spectral domain measures. BSD has become a good candidate for a highly correlated objective quality measure according to several researchers [Lam et al., 1996] [Meky and Saadawi, 1996] [Voran and Sholl, 1995]. The BSD measure is based on the assumption that speech quality is directly related to speech loudness, which is a psychoacoustical term defined as the magnitude of auditory sensation. In order to calculate loudness, the speech signal is processed using the results of psychoacoustic measurements, which include critical band analysis, equal-loudness preemphasis, and intensity-loudness power law.

BSD estimates the overall distortion by using the average Euclidean distance between loudness vectors of the reference and of the distorted speech. When BSD was used initially, the non-silence portions composed of voiced and unvoiced regions were processed. It was found that its performance was enhanced when only the voiced portions are considered in the estimation of distortion. Later versions of the algorithm processed only voiced segments.

Wang et al. (1992) were motivated by the method of calculating an objective measure for signal degradation based on the measurable properties of auditory perception [Schroeder et al., 1979], and developed the Bark Spectral Distortion (BSD) measure [Wang et al., 1992].

Their approach is outlined below. First, a nonlinear frequency transformation from Hertz, *f*, to bark, *b*, is made via the relation [Schroeder et al., 1979]

$$f = 600\sinh(b/6) \tag{15}$$

which transforms the original power spectral density function *X(f)* to a critical band density function *Y(b)*. The function *Y(b)* is smeared by a prototype critical band filter *F(b)* given by [Bladon, 1981]:

$$10\log_{10} F(b) = 7 - 7.5(b-a) - 17.5\left[0.196 + (b-a)^2\right]^{0.5} \tag{16}$$

with a = 0.215. The smearing is conceived of as a convolution operation between *F(b)* and *Y(b)* which yields a continuous spectrum *D(b)*. The fact that the ear is not equally sensitive to the amount of energy at different frequencies is exploited next. The well-known equal loudness level curves [Robinson and Dadson, 1956]

have been used to translate the sound pressure level (SPL) in dB to loudness levels in *phons*. The increase of approximately 10 *phons* of loudness level is required to make the subjective loudness double for the loudness level greater than 40 phons. A *phon-to-sone* conversion is performed using Eq. (14) to generate a Bark spectrum *S(i)*. Then, the BSD measure is defined as the average of $BSD^{(k)}$ with

$$BSD^{(k)} = \sum_{i=1}^{N} \left[S_x^{(k)}(i) - S_y^{(k)}(i) \right]^2 \qquad (17)$$

where N is the number of critical bands, and $S_x^{(k)}(i)$ and $S_y^{(k)}(i)$ are the Bark Spectra in the *i-th* critical band for the *k-th* frame corresponding to the original and the distorted speech, respectively.

BSD works well in cases where the distortion in voiced regions represents the overall distortion, because it processes voiced regions only; for this reason, voiced regions must be detected. BSD uses a traditional metric, Euclidean distance, in the cognition module, but the developers did not validate the use of this metric.

2.2.4.2. Perceptual Speech Quality Measure (PSQM)

PSQM was developed by PTT Research in 1994 [Beerends and Stemerdink, 1994]. It can be considered as a modified version of the Perceptual Audio Quality Measure (PAQM) which is an objective audio quality measure also developed at PTT Research [Beerends and Stemerdink, 1992]. Recognizing that the characteristics of speech and music are different, PSQM was optimized for speech by modifying some of the procedures of PAQM. PSQM has been adopted as ITU-T Recommendation P.861 [ITU-T Recommendation P.861, 1996]. Its performance has been shown to be relatively robust for coding distortions.

PSQM transforms the speech signal into the loudness domain, modifying some parameters in the loudness calculation in order to optimize performance. PSQM does not include temporal or spectral masking in its calculation of loudness. PSQM applies a nonlinear scaling factor to the loudness vector of distorted speech. The scaling factor is obtained using the loudness ratio of the reference and the distorted speech in three frequency bands. The difference between the scaled loudness of the distorted speech and the loudness of the reference speech is called noise disturbance. The final estimated distortion is an averaged noise disturbance over all the frames processed. PSQM disregards or applies a small weight to silence portions in the calculation of distortion.

PSQM uses psychoacoustic results of loudness calculation to transform speech into the perceptually relevant domain. It modifies the procedure of loudness calculation in order to optimize its performance. This modification could be justified by considering that in psychoacoustic experiments, steady-state signals (sinusoids) were used instead of real speech. PSQM also considers the role of distortions in silence portions on overall speech quality. Even though its performance is relatively robust over coding distortions, its performance may not be robust enough to apply to a broader range of distortions.

2.2.4.3. PSQM+

PSQM+ was developed by KPN Research in 1997 [Beerends, 1997]. The performance of PSQM+ is improved over that of the P.861 (PSQM) for loud distortions and temporal clipping by some simple modifications to the cognition module. PSQM+ can be applied to a wider range of distortions as an objective measure than PSQM.

PSQM+ uses the same perceptual transformation module as PSQM. Similar to PSQM, PSQM+ transforms the speech signal into the modified loudness domain, and does not include temporal or spectral masking in its calculation of loudness. In order to improve the performance for the loud

distortions like temporal clipping, an additional scaling factor is introduced when the overall distortion is calculated. This scaling factor makes the overall distortion proportional to the amount of temporal clipping distortion. Otherwise, the cognition module is the same as PSQM.

PSQM+ adopts a simple algorithm in the cognition module to improve the performance of PSQM. The poor performance of PSQM for distortions like temporal clipping is caused by the procedure calculating a scaling factor. The scaling factors are determined by the ratio of the energy of the distorted speech and the reference speech. This scaling factor scheme of PSQM works very well when a distortion results in additional energy. However, if a distortion results in reduced energy such as temporal clipping, which removes some of the signal energy, the estimate of distortion is proportionally smaller, and PSQM underestimates the actual distortion. Therefore, PSQM+ uses a simple modification to adopt an additional scaling factor to compensate for this effect.

PSQM+ resolves one performance issue of PSQM on distortions such as temporal clipping. However, the performance of PSQM+ may be questioned for other different types of distortions.

2.2.4.4. Measuring Normalizing Blocks (MNB)

MNB was developed at the US Department of Commerce in 1997 [Voran, 1997]. It emphasizes the important role of the cognition module for estimating speech quality. MNB models human judgment on speech quality with two types of hierarchical structures. It has showed relatively robust performance over an extensive number of different speech data sets.

MNB transforms speech signals into an approximate loudness domain through frequency warping and logarithmic scaling. MNB assumes that these two factors play the most important role in modeling human auditory response. The algorithm generates an approximated loudness vector for each frame. MNB considers human listener's sensitivity to the distribution of distortion, so it uses hierarchical structures that work from larger time and frequency scales to smaller time and frequency scales. MNB employs two types of calculations in deriving a quality estimate: time measuring normalizing blocks (TMNB) and frequency measuring normalizing blocks (FMNB). Each TMNB integrates over frequency scales and measures differences over time intervals while the FMNB integrates over time intervals and measures differences over frequency scales. After calculating 11 or 12 MNBs, these MNBs are linearly combined to estimate overall speech distortion. The weights for each MNB were optimized with a training data set.

Since there has been little research on the cognition model in the evaluation of speech quality, some procedures of MNB are not fully understood. MNB does not generate a distortion value for each frame since each MNB is integrated over frequency or time intervals. Its performance may depend upon the scope of training data sets.

2.2.4.5. Perceptual Analysis Measurement System (PAMS)

PAMS was developed by British Telecom (BT) in 1998 [Hollier and Rix, 1998]. PAMS aims to achieve robustness and consistency in predicting subjective ratings by careful extraction and selection of parameters describing speech degradation and constrained mapping to subjective quality.

A parameter set, in which each parameter increases with increasing degradation, is generated. The best set of parameters is selected with a training procedure. The parameter set used in PAMS has not been specified in the literature. A linear mixture of monotonic quadratic functions for the selected parameters is used for mapping to subjective quality. The quadratic functions are constrained to be monotonically increasing with increasing value of parameters. The optimum coefficients of the functions are obtained with a training procedure.

PAMS uses a concept of mapping from the parameter domain to subjective quality domain. PAMS describes a general approach in predicting subjective quality. It is flexible in adopting other parameters if they are perceptually important.

The performance of the PAMS depends upon the designer's intuition in extracting candidate parameters as well as selecting parameters with a training data set. Since the parameters are usually not independent of each other, it is not easy to optimize both the parameter set and the associated mapping function. So, extensive computation is performed during training.

2.2.4.6. QVoice

QVoice was developed by ASCOM for predicting speech quality in mobile communication systems. QVoice uses artificial neural networks and fuzzy logic techniques to estimate listener's judgment of subjective quality. It is a popular tool used to test mobile communications systems in the field.

Unlike other perceptual domain measures, QVoice considers the LPC cepstral coefficients over a fixed duration of speech sample (5 seconds) as perceptually significant parameters. The difference between the LPC cepstral coefficient matrices of the reference and distorted speech is fed into a trained

artificial neural network to estimate degradation. Fuzzy logic is used to predict the subjective score using the estimated degradation. Nonlinear processing of listeners' judgment of speech quality is emulated by artificial neural network and fuzzy logic. The parameters of the cognition module are optimized by training the system with speech samples and associated subjective ratings data.

The motivation for using LPC cepstral coefficients for parameters has not been validated in QVoice. It can only estimate the overall speech quality, and does not provide any estimate of the temporal variations of speech quality. Since a neural network technique is used, its performance strongly depends upon the similarity between the test cases making up the samples and training data.

2.2.4.7. Telecommunication Objective Speech Quality Assessment (TOSQA)

TOSQA was developed by Deutsche Telekom (DT) Berkom in 1997 [Berger, 1997]. TOSQA considers the special feature of the MOS test, where subjects compare the speech being tested with a mental reference rather than comparing it to the original (undistorted) speech.

TOSQA calculates a modified reference loudness pattern of the original speech. In this reference pattern, the loudness components which have little influence on speech quality are reduced. TOSQA uses a dynamic frequency

warping to obtain the bark spectrums. The distortion value in TOSQA is based on the similarity between reference and distorted speech rather than the distance between them.

TOSQA has been designed to take into account the structural difference between the MOS test and objective speech quality measures. However, Berger did not explain how to identify the perceptually irrelevant components [Berger, 1997].

CHAPTER 3

EVALUATION OF OBJECTIVE SPEECH QUALITY MEASURES

A reliable evaluation of any system is generally an essential part for development and improvement of that system. The task of evaluating the validity of objective speech quality measures is discussed in this chapter. Since the goal of objective speech quality measures is to replace subjective procedures, the predictability of the latter by the former is an appropriate vehicle for evaluation [Quackenbusch et al., 1988].

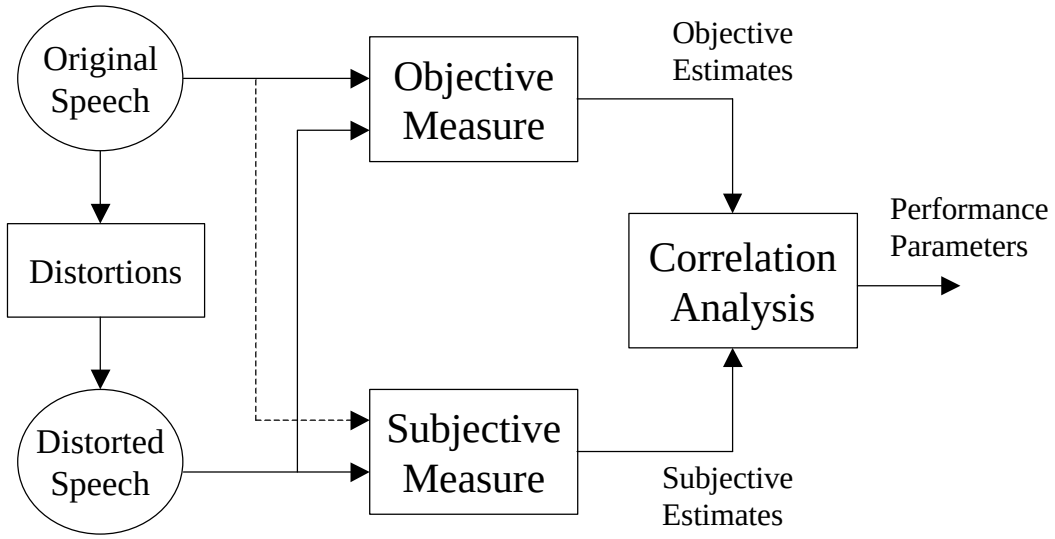


Figure 5. A System for Evaluating Performance of Objective Speech Quality Measures.

A system for evaluating the performance of objective speech quality measures can be described as shown in Figure 5. Original speech is usually a set of phonetically balanced sentences spoken by both males and females. Distorted speech is generated by processing the original speech through various distortion conditions. These distortion conditions can be coding distortions, channel impairments, amplitude variations, temporal clipping, delays, and so on. Although an ideal objective speech quality measure would be able to assess the quality of speech without access to the original speech, current objective speech quality measures base their estimates on both the original and distorted speech. Subjective speech quality measures can estimate the quality of speech with only the distorted speech, or with both the original and distorted speech (described by the broken line in Figure 5) according to the test method used. For instance, the MOS test estimates the quality of the distorted speech with the distorted speech only, while the DMOS test estimates the quality of the distorted speech with both the original and distorted speech. Objective speech quality measures have been conventionally evaluated using MOS scores. However, objective speech quality measures estimate subjective scores by comparing the distorted speech to the original speech. This approach has much more in common with a DMOS test than a MOS test. Therefore, it is worthwhile to examine the performance of objective speech quality measures with DMOS as well as MOS.

After an objective speech quality measure is applied to the original and distorted speech, statistical analysis is performed to determine how well the objective speech quality measure predicts the subjective test results. The correlation coefficient between the objective speech quality measures and the subjective speech quality measures has been conventionally used as a figure-of-merit for comparing objective speech quality measures. However, the correlation coefficient has some shortcomings that can be compensated by considering some additional measures of performance. Therefore, another figure-of-merit, the standard error of the estimate (SEE), is employed to compensate for those shortcomings of the correlation coefficient. The SEE is an unbiased statistic for estimating of the deviation from the best-fitting curve between two variables. The SEE has several advantages over the correlation coefficient as a figure-of-merit for evaluation of objective speech quality measures, as will be discussed later.

3.1. Evaluation With MOS Versus DMOS

A good objective speech quality measure should estimate the quality of a distorted speech accurately. However, how can we verify that an objective speech quality measure is good? The answer to this question is to compare the

estimated quality of an objective measure with the actual quality of a distorted speech set obtained from subjective tests. Since the MOS test is the most widely used subjective test in the speech coding community, the performance of objective speech quality measures has been assessed with the correlation between these measures and the MOS scores. No one has raised a question as to the validity of using MOS scores for the evaluation of objective speech quality measures simply because the goal of objective speech quality measures was to predict the MOS scores. However, when we compare the procedure of the MOS test and the basic approach of objective speech quality measures, there is a procedural difference between them. In a MOS test, listeners are not provided with an original speech sample, and rate the overall speech quality of the distorted speech sample. However, objective speech quality measures estimate subjective scores by comparing the distorted speech to the original speech, as discussed before. Although this procedural difference between objective speech quality measures and the MOS test has been noted in the literature [Yang et al., 1997] [Berger, 1997] [Yang et al., 1998] [Voran, 1999], there has been no attempt to apply this information to the evaluation of objective speech quality measures. This procedural difference can result in incorrect evaluation of objective speech quality measures, especially when the original speech samples are degraded. As a simple illustration, assume that original speech degraded by background noise

is transmitted through a transparent system, so that the output speech is exactly the same as the input speech, as shown in Figure 6.

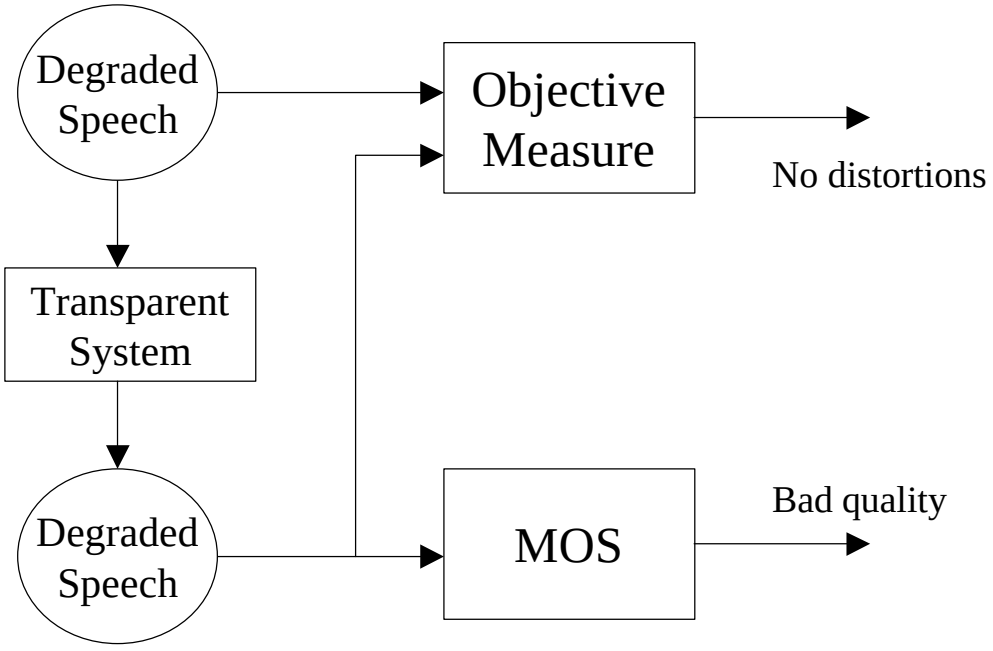


Figure 6. A System Illustrating the Procedural Difference Between Objective Measures and the MOS Test: When the Degraded Reference Speech is Transmitted by a Transparent System.

For this situation, the objective speech quality measure will regard the quality of the output speech as “excellent” because there is no degradation. However, the MOS scores of the output speech would be classified as “bad”. This discrepancy has nothing to do with the actual performance of objective speech quality

measure, rather it is caused by the procedural difference between the MOS [absolute category rating (ACR)] and the DMOS [degradation category rating (DCR)].

In order to exclude the problem of procedural difference, it has been proposed that the DCR subjective test would be more appropriate for evaluation of objective speech quality measures because the approach of objective speech quality measures is analogous to that of DMOS [Yang et al., 1997] [Yang et al., 1998] [Yang and Yantorno, 1999]. In the evaluation of objective speech quality measures, Yang et al. (1998) used MOS difference data (MOS of original speech – MOS of distorted speech) instead of DMOS data because no DMOS data were available. They compared the correlation coefficients of prospective objective speech quality measures with the MOS as well as with the MOS difference for each speech file [Yang and Yantorno, 1999]. It should be noted that the objective speech quality measures used in this experiment showed better correlation with the MOS difference than with the MOS, as shown in Table 4.

Table 4. Correlation Coefficients with the MOS and the MOS Difference for Speech Coding Distortion (Correlation Analyses with each Speech Sample) [Yang and Yantorno, 1999]

Objective Measures	MOS	MOS difference
PSQM	0.8731	0.8933
MNB1	0.7958	0.8319
MNB2	0.8140	0.8478
MBSD	0.8782	0.9001
MBSD II	0.9041	0.9252

Recently, current perceptual objective speech quality measures have been evaluated with both MOS and DMOS at Nortel Networks in Ottawa [Thorpe and Yang, 1999]. The results have shown that current objective speech quality measures are better correlated with DMOS scores than with MOS scores. The results have been summarized in Figure 7. These results suggest that a DCR subjective test such as DMOS is more appropriate for evaluation of objective speech quality measures due to the procedural difference between objective speech quality measures and the MOS test. This observation also provides insight into the development of a new model for objective speech quality measures appropriate in real network applications which will be discussed later.

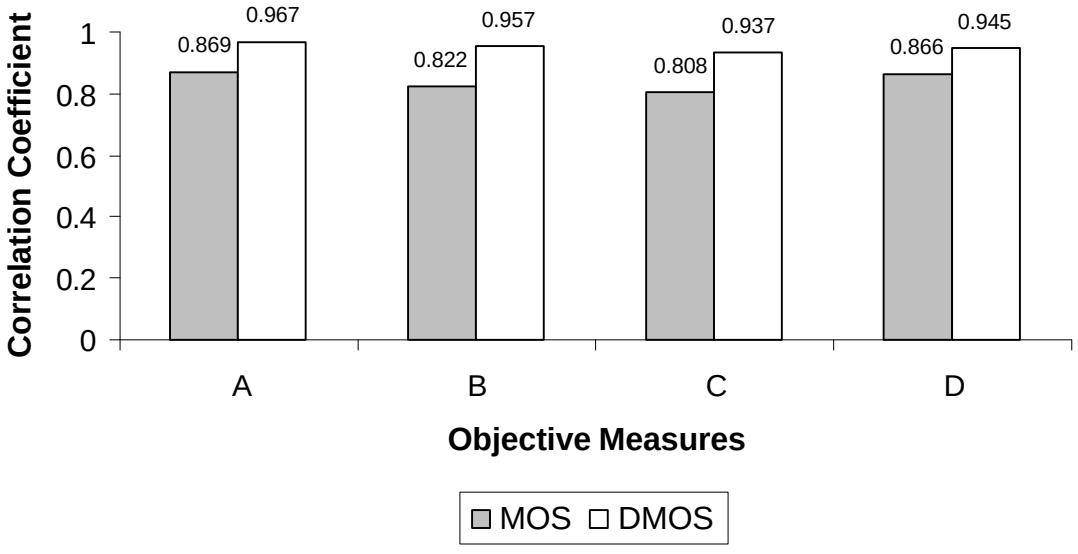


Figure 7. Performance of Current Objective Quality Measures with both MOS and DMOS [Thorpe and Yang, 1999].

3.2. Correlation Analysis

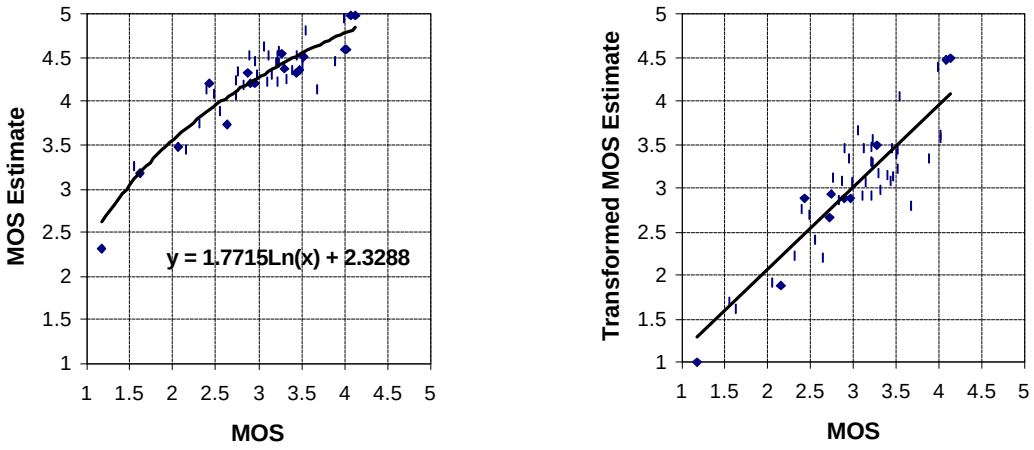
After an objective speech quality measure is applied to the original and distorted speech to generate the estimates of subjective scores, statistical analysis is performed to determine how well it predicts the subjective test results. The correlation coefficient has been conventionally used as a performance parameter for evaluation of objective speech quality measures. The correlation coefficient (also called Pearson product-moment correlation) is formulated as

$$r = \frac{N\sum_{i=1}^{N} X(i)Y(i) - \left(\sum_{i=1}^{N} X(i)\right)\left(\sum_{i=1}^{N} Y(i)\right)}{\left[\left(N\sum_{i=1}^{N} X(i)^2 - \left(\sum_{i=1}^{N} X(i)\right)^2\right)\left(N\sum_{i=1}^{N} Y(i)^2 - \left(\sum_{i=1}^{N} Y(i)\right)^2\right)\right]^{1/2}} \tag{18}$$

where $X(i)$ are the subjective scores, $Y(i)$ are the corresponding objective estimates, and N is the number of distortion conditions.

Since this correlation analysis assumes that the two measures are linearly related, pre-processing is required before calculating the correlation coefficient if the two measures are not linearly related. If the two measures are not linearly related, as shown in Figure 8 (a), the best monotonic fitting function between them is obtained from regression analysis. Figure 8 (b) shows the scatterplot of

the measure after the estimates of the objective measures are transformed with the regression curve. Then, the correlation coefficient between the subjective measures and the transformed estimates of the objective measure is calculated using Eq. (18). The closer to +1 the correlation coefficient is, the better the objective speech quality measure is at predicting the subjective rating.



(a) (b)

Figure 8. Transformation of Objective Estimates With a Regression Curve; (a) Objective Estimates and Subjective Estimates are not Linearly Related, (b) Objective Estimates are Transformed With the Regression Curve.

The correlation coefficient has some shortcomings. Comparing performance with the different groups of conditions is difficult because the

groups may have different types of distortions, different value ranges, and small numbers of data points. Also, the correlation coefficient is highly sensitive to outliers. For the same reasons, it would be inappropriate to compare the correlation coefficients of an objective speech quality measure for different speech data. The shortcomings outlined above can be overcome by considering another performance parameter, the standard error of the estimates.

3.3. Standard Error of Estimates (SEE)

The standard error of the estimates (SEE) can compensate for some shortcomings of the correlation coefficient as a figure-of-merit. The SEE is an unbiased statistic for the estimate of the deviation from the regression line between objective estimates and the actual subjective scores. The SEE is defined as

$$S_{est} = \sqrt{\frac{\sum_{i=1}^{N} \left(Q_o(i) - Q_s(i)\right)^2}{N-2}} \qquad (19)$$

where the $Q_o(i)$ are the objective estimates, the $Q_s(i)$ are the subjective ratings, and N is the number of data points. The SEE is the square root of the average squared error of prediction of objective measures, representing the accuracy of prediction.

The SEE can be obtained from the standard deviation (s_s) of the subjective scores and the correlation coefficient (r) between the objective estimates and the subjective scores. An alternate formula for the SEE is

$$S_{est} = s_s \sqrt{(1-r^2)} \sqrt{\frac{N}{N-2}} \qquad (20)$$

where N is the number of data points. The SEE is related to the correlation coefficient as well as the standard deviation of the subjective scores. For the same correlation coefficient, the SEE tends to decrease as the variation of the subjective scores gets smaller and the number of data points increases.

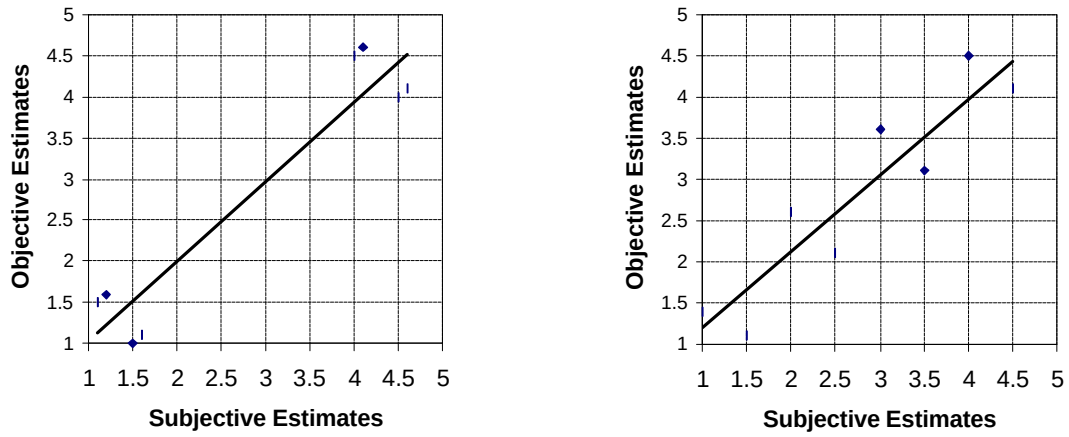
The SEE value characterizes predictability of objective speech quality measures in terms of the error of the subjective scores in a statistically meaningful way. The SEE value (S_{est}) would lead to the expectation that for a given objective speech quality measure, the estimated subjective scores of approximately 68% of the new speech samples will fall between $\pm S_{est}$ of their actual subjective scores. Extending the range to twice S_{est}, it is expected that

approximately 95% of objective estimates will fall between $\pm 2S_{est}$ of their actual subjective scores. In other words, the SEE provides the performance of an objective speech quality measure in terms of confidence interval of objective estimates. This information would be very useful to users who want to understand the capability of an objective speech quality measure to predict subjective scores.

The SEE has another advantage over the correlation coefficient as a figure-of-merit. Since it considers the distribution of the subjective scores of a speech data base, the SEE of the objective measure with one set of data can be compared to that with another set, which may not be valid for the correlation coefficient. Also, the SEE with a certain condition group can be compared to that with a different condition group, using Eq. (19). These kinds of comparisons would be very useful to analyze the performance of the objective speech quality measures, suggesting that the SEE would be a valuable figure-of-merit. Although the SEE has been mentioned as an appropriate figure-of-merit [Quackenbusch et al., 1988], it has not been used widely.

The advantages of the SEE as a figure-of-merit over the correlation coefficient can be illustrated with the following simple illustration. Figure 9 shows two scatterplots of an objective speech quality measure with two different sets of data. The speech data of Figure 9 (a) have a relatively large standard

deviation of subjective estimates (s_{sa} = 1.60) while the speech data of Figure 9 (b) have a relatively small standard deviation (s_{sb} = 1.22).



(a) (b)

Figure 9. Scatterplots of an Objective Measure With Two Different Sets of Speech Data; (a) Speech Data With a Relatively Large Standard Deviation, (b) Speech Data With a Relatively Small Standard Deviation.

The correlation coefficients of the objective measure are 0.95 with speech data set (a), and 0.92 with speech data set (b). However, the SEE values of the objective measure are 0.57 for speech data set (a), and 0.51 for speech data set (b). The correlation coefficient with speech data set (a) has increased due to the relatively large standard deviation although the prediction error with speech data set (a) is

larger than that with speech data set (b). So, it is not meaningful to compare the correlation coefficients of the objective measure with different speech data. Since SEE considers the distribution of the subjective scores of a speech data, it is possible to compare performance of an objective measure with different speech data using the SEE values.

When the performance of the objective measure is analyzed for a certain condition group, the correlation coefficient calculated with the data points of that group is not meaningful because the range of subjective scores, as well as the number of data points in a group, are usually small. More importantly, this analysis cannot consider the regression line of all data points. This phenomenon is illustrated with Figure 10. The correlation coefficient of all of the data points is 0.87 while the correlation coefficient of the square data points is -0.86. It is evident that this correlation coefficient of the square points themselves is meaningless. However, it is possible to determine how much errors the objective measure may make for the square data points by comparing the SEE of the square data points (1.14) with that of all the data points (0.58).

As shown above with illustrations, the SEE will be a valuable figure-of-merit to analyze the performance of objective speech quality measures. The SEE characterize predictability of objective speech quality measures. Using the SEE, it is possible to compare performance of an objective quality measure with one set of speech data set to that with other speech data set.

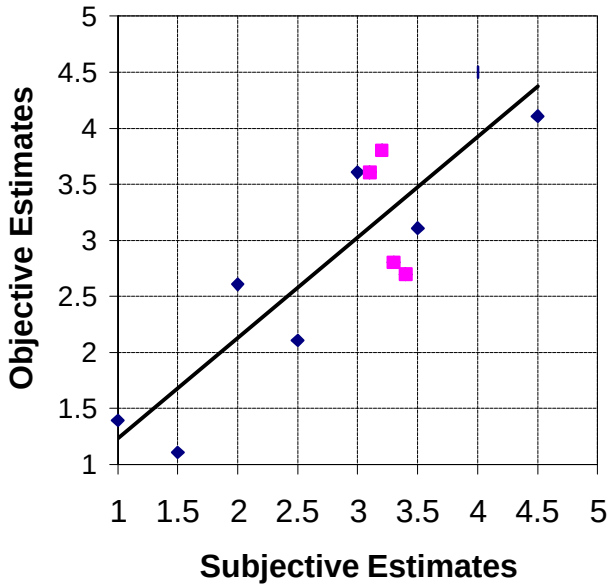


Figure 10. Scatterplot Illustrating That Correlation Coefficient of a Certain Condition Group (Square Points).

CHAPTER 4

MODIFIED BARK SPECTRAL DISTORTION (MBSD)

The MBSD has been developed in the Speech Processing Lab at Temple University [Yang et al., 1997] [Yang et al., 1998]. It can be classified as a perceptual domain measure that transforms the speech signal into a perceptually relevant domain which incorporates human auditory models. The MBSD is a modification of the BSD [Wang et al., 1992] in which the concept of a noise masking threshold is incorporated, that differentiates audible and inaudible distortions. The MBSD uses the same noise masking threshold as that used in transform coding of audio signals [Johnston, 1988]. The MBSD assumes that loudness differences below the noise masking threshold are not audible and therefore are excluded in the calculation of the perceptual distortion. This new addition of the noise masking threshold replaces the empirically derived distortion threshold value used in the BSD.

This chapter begins with the description of major processing modules of the MBSD measure. The performance of the MBSD is examined with several different types of experiments. First, various different distortion metrics are examined to search for a proper metric to be used in the MBSD measure. Second, the effect of the noise masking threshold for the performance of the MBSD is illustrated. Third, the performance of the MBSD is investigated with various

frame sizes and different speech classes (voiced, unvoiced, and transient). All of these experiments were performed with a speech database where distortions were caused by various coders. This database was provided by Lucent Technologies.

4.1. Algorithm of MBSD

The block diagram of the MBSD measure is shown in Figure 11 [Yang et al., 1997]. The MBSD computes the distortion frame by frame, with the frame length of 320 samples using 50% overlap. Each frame is weighted by a Hanning window, and *x(n)* and *y(n)* denote the *n-th* frame of the original and distorted speech, respectively. $L_x(n)$ and $L_y(n)$ are the loudness vectors of the *n-th* frame of the original and distorted speech, respectively. $D_{xy}(n)$ is the loudness difference between $L_x(n)$ and $L_y(n)$, and *NMT(n)* is the noise masking threshold calculated from the original speech.

In order to compute the perceptual distortion of the *n-th* frame, MBSD(n), an indicator of perceptible distortion of the *n-th* frame, *M(n,i)*, is used where *i* is the *i-th* critical band. When the distortion is perceptible, *M(n,i)* is 1, otherwise *M(n,i)* is 0.

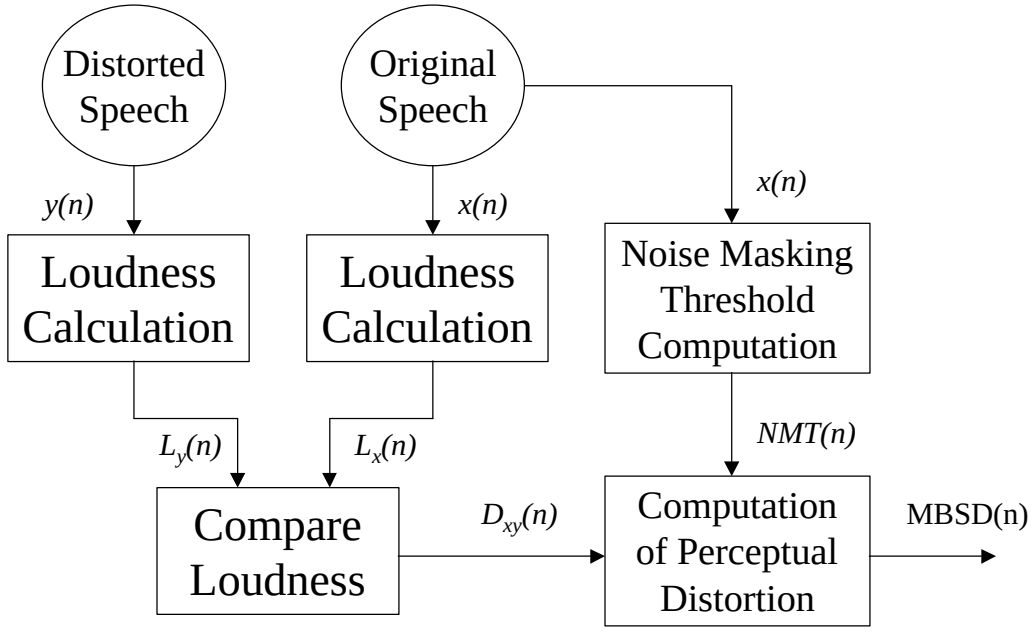


Figure 11. Block Diagram of the MBSD Measure.

The indicator of perceptible distortion is obtained by comparing the *i-th* loudness difference of the *n-th* frame ($D_{xy}(n,i)$) to the noise masking threshold ($NMT(n,i)$) as follows

$$M(n,i) = 0, \quad \text{if } D_{xy}(n,i) \leq NMT(n,i) \tag{21.1}$$

$$M(n,i) = 1, \quad \text{if } D_{xy}(n,i) > NMT(n,i) \tag{21.2}$$

The perceptual distortion of the *n-th* frame is defined as the sum of the loudness difference which is greater than the noise masking threshold and is formulated as:

$$MBSD(n) = \sum_{i=4}^{18} M(n,i) D_{xy}(n,i) \qquad (22)$$

where $M(n,i)$ and $D_{xy}(n,i)$ denote the indicator of perceptible distortion and the loudness difference in the *i-th* critical band for the *n-th* frame, respectively. $MBSD(n)$ is the perceptual distortion of the *n-th* frame. The first three loudness components have not been used in calculating the distortion of a frame, because these components are assumed to be filtered out in wired telephone networks. The final MBSD value is calculated by averaging the $MBSD(n)$ using only the non-silence frames.

There are two major processing steps in the MBSD algorithm: loudness calculation and noise masking threshold computation. The loudness calculation transforms speech signal into loudness domain. In order to transform a non-silence frame into loudness domain, a frame is processed as follows: (i) critical band analysis, (ii) application of spreading function, (iii) equal-loudness preemphasis in loudness level (phon), and (iv) transformation of loudness level

(phon) into loudness scale (sone). The actual MBSD programs are given in Appendix A (Matlab code).

(i) **Critical band analysis**

After the power spectrum of a non-silence frame is obtained using FFT, the power spectrum is then partitioned into critical bands, according to Table 3 in Chapter 2. Since the bandwidth of telephone networks is approximately 3.4 kHz, 18 critical bands are used for the MBSD calculations. The energy in each critical band is summed as

$$B(i) = \sum_{f=f_l}^{f_u} P(f) \qquad \text{for } i = 1 \text{ to } 18 \qquad (23)$$

where f_l is the lower boundary of critical band i, f_u is the upper boundary of critical band i, $P(f)$ is the power spectrum, and $B(i)$ is the energy in critical band i.

(ii) **Application of spreading function**

The spreading function is used to estimate the effects of masking across critical bands [Schroeder et al., 1979].

First, a matrix $S(i,j)$ is calculated for the spreading function as

$$S(i,j) = 15.81 + 7.5(i - j + 0.474) - 17.5\sqrt{1 + (i - j + 0.474)^2} \text{ , for } |j - i| \le 25 \qquad (24)$$

where *i* is the bark frequency of the masked signal, and *j* is the bark frequency of the masking signal.

Then, the critical band spectrum, *B(i)*, is multiplied with *S(i,j)* as follows

$$C(i) = \sum_{j=1}^{18} S(i,j)B(j) \qquad (25)$$

The value of *C(i)* denotes the spread critical band spectrum of *i-th* critical band.

(iii) **Equal-loudness preemphasis in loudness level**

After obtaining the spread critical band spectrum, it is converted into dB scale and the loudness level of each critical band is obtained according to the equal-loudness contours as shown in Figure 4. Data points in between the contours are interpolated. The actual dB scales of each critical band for loudness levels can be found in the programs of Appendix A.

(iv) **Transformation of loudness level (phon) into loudness scale (sone)**

As a final step, the spread critical spectrum in loudness level is transformed into loudness scale [Bladon, 1981]

$$L(i) = \left(\frac{D(i)}{40} \right)^{2.642} \qquad \text{if } D(i) < 40 \tag{26.1}$$

$$L(i) = 2^{0.1(D(i)-40)} \qquad \text{if } D(i) \geq 40 \tag{26.2}$$

where *L(i)* is the loudness of the critical band *i*, and *D(i)* is the spread critical spectrum in loudness level of the critical band *i*.

The noise masking threshold is estimated by critical band analysis, spreading function application, the noise masking threshold calculation, and absolute threshold consideration [Johnston, 1988]. The first two procedures are the same as described above. The noise masking threshold calculation considers tone masking noise and noise masking tone [Scharf, 1970] [Hellman, 1972] [Schroeder et al., 1979].

Tone-masking noise is estimated as *(14.5 + i)* dB below the spread critical spectrum in dB, *C(i)*, where *i* is the bark frequency. The noise masking a tone is estimated as 5.5 dB below *C(i)* uniformly across the spread critical spectrum. In order to apply the tone masking noise and the noise masking tone, the Spectral Flatness Measure (SFM) is used to determine if the signal is close to noise or tone. The SFM is defined as the ratio of the geometric mean (*Gm*) of the power spectrum to the arithmetic mean (*Am*) of the power spectrum. The SFM is converted into decibels as follows

$$SFM_{dB} = 10\log_{10}\frac{Gm}{Am} \tag{27}$$

and a coefficient of tonality, α is defined as

$$a = \min\left(\frac{SFM_{dB}}{SFM_{dB\max}},1\right) \tag{28}$$

where SFM_{dBmax} is set to –60 dB for the entirely tonelike signal. An SFM_{dB} of 0 dB indicates a signal that is completely noiselike.

The offset (*O(i)*) in decibels for the masking energy in each critical band is calculated using the coefficient of tonality, α as

$$O(i) = a(14.5 + i) + (1 - a)5.5 \tag{29}$$

The coefficient of tonality, α, is used to weight geometrically the two threshold offsets, (14.5 + *i*) dB for tone masking noise and 5.5 dB for noise masking tones.

The noise masking threshold is obtained by subtracting the offset (*O(i)*) from the spread critical spectrum (*C(i)*) in dB. If any critical band has a calculated noise masking threshold lower than the absolute threshold, it is changed to the absolute threshold for that critical band.

4.2. Search for a Proper Metric of MBSD

There are two major differences between the conventional BSD and the MBSD. First, the MBSD uses the noise masking threshold for the determination of audible distortion, while the BSD uses an empirically determined power threshold. Second, the computation of distortion in the BSD is different from that of the MBSD. In the BSD, the squared Euclidean distance was used for the distortion metric, but it was never determined if this was the most appropriate metric. In order to determine a proper metric, which will match the human perception of distortion in the MBSD, various metrics were examined [Yang et al., 1998]. These metrics were limited by the variations of the first and the second norms. For the experiments, the following equation was used:

$$MBSD = \frac{1}{N}\sum_{n=1}^{N}\left[\sum_{i=1}^{K} M(n,i)\left(D_{xy}(n,i)\right)^{m}\right] \qquad (30)$$

where N is the number of the frames processed, K is the number of critical bands, $M(n,i)$ is the *i-th* indicator of perceptual distortion of the *n-th* frame, and $D_{xy}(n,i)$ is the *i-th* loudness difference of the *n-th* frame. The results of the experiments are summarized in Table 5. These results indicate the importance of a proper metric. Depending on the metric, the correlation coefficient could vary from 0.01 to 0.03.

The average difference of estimated loudness showed the highest correlation coefficient. So, it was decided that the MBSD would use the average difference of the estimated loudness as a metric.

Table 5. Performance of the MBSD for Various Metrics

Metric	Correlation Coefficient
Loudness difference (m=1 in Eq. (30))	0.94
Squared loudness difference (m=2 in Eq. (30))	0.93
Normalized loudness difference	0.92
Normalized squared loudness difference	0.91

4.3. Effect of Noise Masking Threshold in MBSD

Since the MBSD uses the noise masking threshold, which determines if the distortion is perceptible, it is worthwhile to examine the effect of the noise masking threshold on the performance of the MBSD. In order to examine the effect of the noise masking threshold, the performance of the MBSD without the noise masking threshold is compared to that with the noise masking threshold. The estimated distortion for the MBSD without the noise masking threshold has been computed by setting the indicator of perceptible distortion, $M(n,i)$, to 1 in the Eq. (22). Figure 12 shows the performance of the MBSD without the noise

masking threshold. According to Figure 12, the MBSD without the noise masking threshold overestimates some distortions because it simply uses the loudness difference without considering perceptual distortion. Figure 13 shows the performance of the MBSD with the noise masking threshold using the same speech data set as used for Figure 12. It shows clearly that the overestimated distortion has been decreased and the MBSD with the noise masking threshold gives a higher correlation with subjective quality measure. Therefore, the noise masking threshold plays an important role in estimating perceptually relevant distortion of objective speech quality measure.

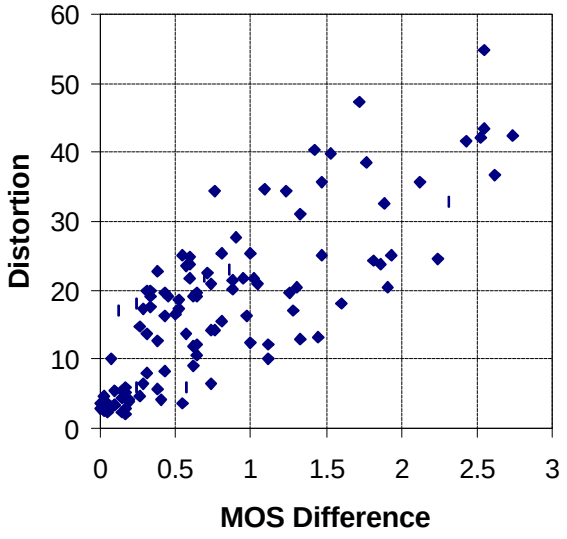


Figure 12. MBSD Versus MOS Difference (Without Noise Masking Threshold [Yang and Yantorno, 1998]).

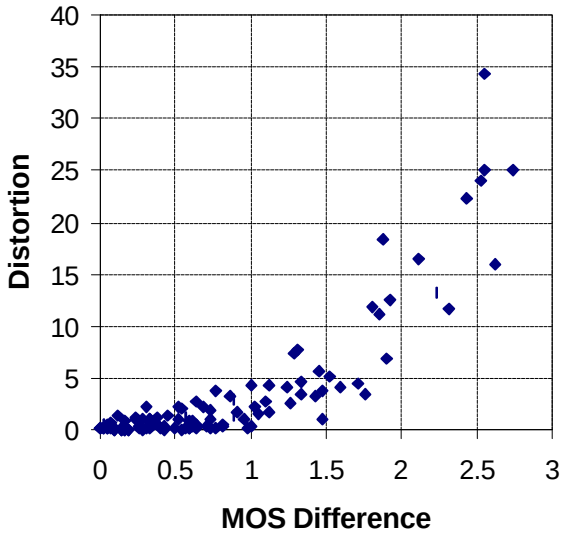


Figure 13. MBSD Versus MOS Difference (With Noise Masking Threshold [Yang and Yantorno, 1998]).

4.4. Performance of MBSD With Coding Distortions

The performance of the MBSD has been examined with different frame sizes and speech classes. Although the BSD showed the better performance by processing voiced regions of a speech utterance, it may not be justifiable to exclude some portions of speech segments. Therefore, it is worthwhile to investigate the performance of the MBSD with different frame sizes and speech classes. Table 6 summarizes the performance of the MBSD with different frame sizes and speech classes. The frame size was varied from 40 samples (corresponding to 5 ms) to 400 samples (corresponding to 50 ms). The speech

signal was classified by hand-labeling: silence, voiced, unvoiced, and transitional regions of speech.

Table 6. Correlation Coefficients of the MBSD with Different Frame Sizes and Speech Classes

Speech Class	FRAME SIZE (samples)					
	40	80	160	240	320	400
Voiced	0.96	0.96	0.96	0.95	0.95	0.95
Unvoiced	0.60	0.66	0.69	0.72	0.74	0.75
Transitional	0.63	0.73	0.79	0.82	0.71	0.67
Non-silence	0.94	0.96	0.96	0.96	0.96	0.95

According to the results, it should be noted that the performance of the MBSD is not very sensitive to the frame size variation in the range between 40 samples and 400 samples for speech classes of voiced and non-silence regions. Since the speech database in these experiments are coding distortions, the performance with voiced regions is almost same as that of the non-silence regions. However, if there are distortions such as bit errors or frame erasures occurring in the unvoiced regions, the MBSD will have a better performance if the non-silence regions are processed. On the other hand, it would be better to process the MBSD with larger frame size if the performance is not very sensitive to frame size in order to reduce computational complexity. So, the MBSD has been programmed to process non-silence regions with a frame size of 320 samples.

CHAPTER 5

IMPROVEMENT OF MBSD

The performance of the MBSD was comparable to the ITU-T Recommendation P.861 for speech data with coding distortions [Yang et al., 1998] [Yang and Yantorno, 1998]. The noise masking threshold calculation is based on psychoacoustic experiments using steady-state signals such as single tones and narrow band noise rather than speech signals. It may not be appropriate to use the noise masking threshold based on psychoacoustic experiments for speech signals which are nonstationary, therefore, the performance of the MBSD has been studied by scaling the noise masking threshold.

Speech coding is only one area where distortions of the speech signal can occur. There are presently other situations where distortions of the speech signal can take place, e.g., cellular phone systems, and in this environment there can be more than one type of distortion. Also, there are other distortions encountered in real network applications, such as codec tandeming, bit errors, frame erasures, and variable delays. Recently, the performance of the MBSD has been examined with TDMA speech data generated by AT&T, in the following ways: use of the first 15 loudness components in the calculation of distortion; development of a new cognition model based on postmasking effects; normalization of loudness

vectors; and deletion of the spreading function in noise masking threshold calculation.

5.1. Scaling Noise Masking Threshold

The MBSD measure estimates perceptible distortion in the loudness domain, taking into account the noise masking threshold used in the transform coding of audio signals [Johnston, 1988]. Since the noise masking threshold plays an important role in the calculation of perceptible distortion of the MBSD, it is worthwhile to examine if the noise masking threshold is valid. Precisely speaking, the use of the psychoacoustically derived noise masking threshold has not been validated for speech. The psychoacoustic results are based on steady-state signals such as sinusoids, rather than speech signals which contain a series of tones. Consequently, the noise masking threshold taken directly from the psychoacoustics literature may not be appropriate for estimating perceptible distortion in speech signals. As a first step in understanding the importance of the role of the noise masking threshold in the objective speech quality measures, the performance of the MBSD has been examined by scaling the noise masking threshold.

In the calculation of the MBSD value, the indicator of the *i-th* perceptible distortion of the *n-th* frame (*M(n,i)*) is determined by comparing the *i-th* loudness difference of the *n-th* frame ($D_{xy}(n,i)$) to the *i-th* noise masking threshold of the *n-th* frame (*NMT(n,i)*). Instead of using the indicator of perceptible distortion as outlined in Eq. (21), a scaling factor (β) was applied to the noise masking threshold as follows:

$$M(n,i) = 0, \quad \text{if } D_{xy}(n,i) \le \beta NMT(n,i) \tag{31.1}$$

$$M(n,i) = 1, \quad \text{if } D_{xy}(n,i) > \beta NMT(n,i) \tag{31.2}$$

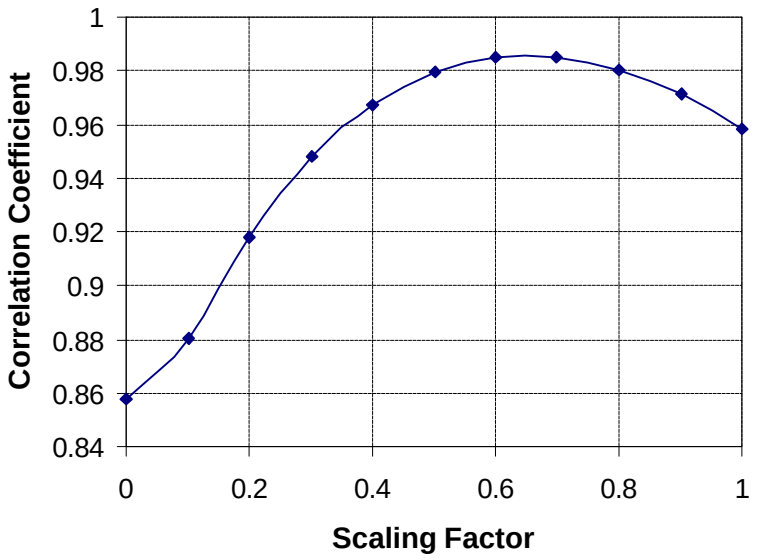


Figure 14. Performance of the MBSD for Speech Data With Coding Distortions Versus the Scaling Factor of the Noise Masking Threshold.

The performance of the MBSD measure has been examined for speech data with coding distortions by varying the scaling factor (β) from 0.0 to 1.0 with a step size of 0.1. Figure 14 shows the relationship between the performance of the MBSD and the scaling factor. A scaling factor of 0.7 gives the highest correlation coefficient [Yang and Yantorno, 1999].

The MBSD measure that uses a scaling factor of 0.7 has been labeled MBSD II. The performance of the MBSD II has been compared with ITU-T Recommendation P.861 and MNB measures. The performance of the MBSD II is slightly better than that of P.861 and MNB II, as shown in Table 7.

Table 7. Correlation Coefficients of MBSD II and Other Measures for Speech Data with Coding Distortions

P.861	MNB I	MNB II	MBSD	MBSD II
0.98	0.97	0.98	0.96	0.99

Table 7 also shows that the MBSD measure is improved by scaling the noise masking threshold (the correlation coefficient has increased by 0.03).

5.2. Using the First 15 Loudness Vector Components

Although the MBSD has been improved by scaling the noise masking threshold for the speech data with various coding distortions [Yang and Yantorno, 1999], it has not been tested with other distortions. When the performance of the MBSD was examined with TDMA data generated by AT&T, the MBSD showed a correlation coefficient of 0.76, which was unsatisfactory. This result has motivated to improve the MBSD by performing the following experiments.

The following experiments described were performed using TDMA data. This data was collected in real network environments, and gave valuable insights to improve the MBSD. Some of the basic aspects of the MBSD algorithm have been tested to determine if they are perceptually important or relevant for the TDMA data, as well as to ensure that any changes had no adverse affects on the MBSD with respect to speech coding distortions.

As described in Chapter 4, the MBSD algorithm did not use the first 3 components of loudness vectors in the calculation of a distortion value, because these components were assumed to be filtered out in wired telephone networks. Since the perceptual importance of these three loudness components has not been tested, the performance of the MBSD is examined with the first 15 loudness components.

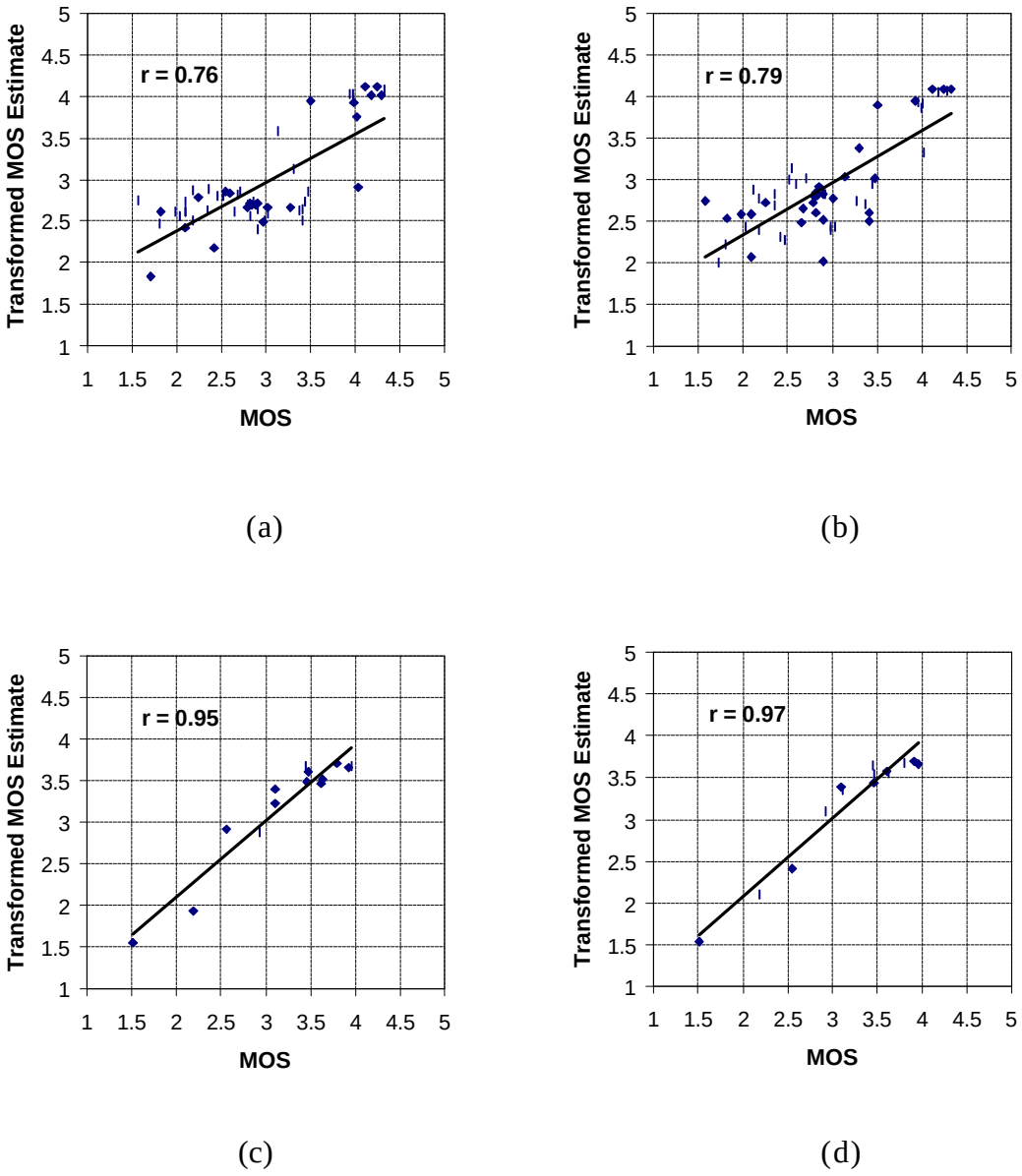


Figure 15. Performance of the MBSD With the First 15 Loudness Components; (a) Performance of the Original MBSD for TDMA Data, (b) Performance of the MBSD With the First 15 Loudness Components for TDMA Data, (c) Performance of the Original MBSD for Speech Coding Distortions, (d) Performance of the MBSD With the First 15 Loudness Components for Speech Coding Distortions.

As shown in Figure 15 (a) and (b), the MBSD with the first 15 loudness components showed better correlation than the original MBSD, with an increase in the correlation coefficient of 0.03.

The performance of the MBSD with the first 15 loudness components has also been examined with speech coding distortions. The MBSD with the first 15 loudness components has shown better correlation with the subjective scores for speech coding distortions, as well. Therefore, these results indicate that it is more appropriate to include the first 15 loudness components in the calculation of perceptible distortion. Eq. (22) in the MBSD algorithm is changed as follows

$$MBSD(n) = \sum_{i=1}^{K} M(n,i) D_{xy}(n,i) \qquad (32)$$

where $M(n,i)$ and $D_{xy}(n,i)$ denote the indicator of perceptible distortion and the loudness difference in the *i-th* critical band for the *n-th* frame, respectively. $MBSD(n)$ is the perceptual distortion of the *i-th* frame. K is the number of critical band used in the MBSD measure, and is set to 15.

5.3. Normalizing Loudness Vectors

When the MBSD is used to calculate the loudness difference for a frame, the loudness difference between the distorted and original speech has been obtained without normalizing these loudness vectors. Without normalization of the two loudness vectors, the difference could contain perceptually irrelevant portions. Therefore, the performance of the MBSD is examined using normalization of these loudness vectors. For normalization, the ratio of the total loudness of the original speech frame to the total loudness of the distorted speech frame is used as

$$\overline{L_y(i)} = \frac{\sum_{j=1}^{K} L_x(j)}{\sum_{j=1}^{K} L_y(j)} \left(L_y(i)\right) \qquad \text{for } i = 1, \ldots, K \qquad (33)$$

where *Lx(j)* and *Ly(j)* are the *j-th* component of the loudness vector of original speech and distorted speech, respectively. $\overline{L_y(i)}$ is the *i-th* component of the normalized loudness vector of the distorted speech. *K* is set to 15.

The correlation coefficient of the MBSD with normalization was increased by 0.01. The MBSD with normalization performed slightly better than the MBSD without normalization of loudness vectors.

5.4. Deletion of the Spreading Function in the Calculation of the Noise Masking Threshold

When the noise masking threshold is calculated, the spreading function is applied to estimate the effects of masking across critical bands [Johnston, 1988]. The derivation of this spreading function is based on psychoacoustic experiments using steady-state signals such as sinusoids rather than speech signals. Therefore, it could be worthwhile to perform some experiments with the MBSD in which the noise masking threshold is calculated without the spreading function. The correlation coefficient of the modified MBSD without the spreading function increased by 0.02. Although the improvement was not significant, the spreading function appeared to give adverse affects on the performance of the MBSD.

Although the effects of masking across critical bands play an important role for transform coding of audio signals, these masking effects appear to have adverse affects for the MBSD measure to predict the subjective ratings.

5.5. A New Cognition Model Based on Postmasking Effects

The MBSD uses a simple cognition model to calculate the distortion value. The distortion value for an entire test speech utterance was obtained by averaging over all non-silence frames. This simple cognition model is based on two assumptions: (1) non-silence segments represent speech quality of an entire test speech utterance; in other words, there is no distortion in silence segments or the distortion of silence segments is perceptually the same as that of non-silence segments, and (2) the variance of distortion values in an entire test speech utterance is small enough to be well represented by its mean. The first assumption is often invalid when background noise is added to the reference speech utterance. Most importantly, the second assumption is not valid for distortions such as bit errors or frame erasures encountered in real network environments, where the distortion values are not evenly distributed and more likely to be bursty.

Although the average distortion values of two speech utterances would be the same, human listeners will perceive their speech quality differently depending upon the temporal distribution of the distortion values. As an extreme example, shown in Figure 16, case (A) and (B) have the same average distortion value. However, the temporal distributions of their distortion values are very different. The distortion values of case (A) are evenly distributed, but

case (B) has one large distortion among small distortion values. Human listeners would perceive that case (B) has much more degradation than case (A).

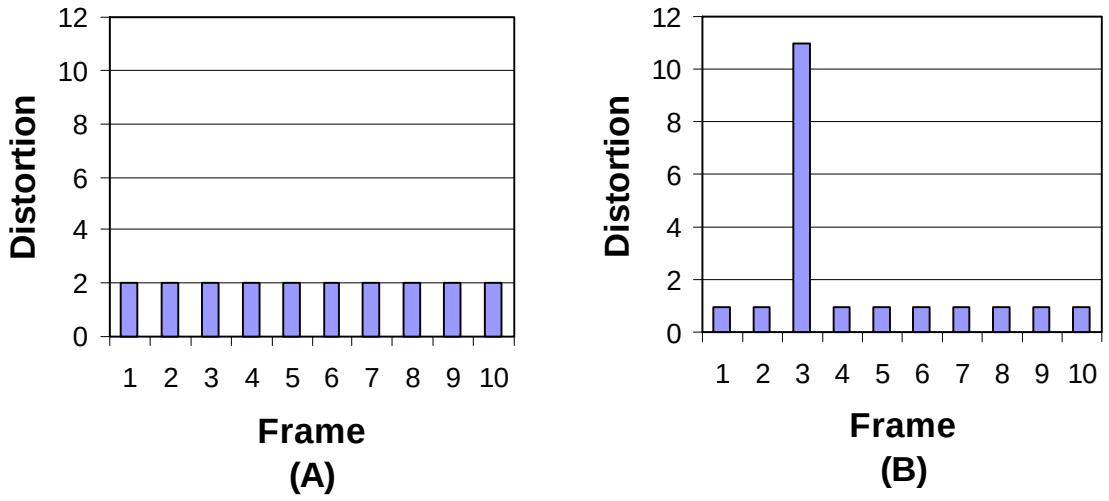


Figure 16. Two Different Temporal Distortion Distributions With the Same Average Distortion Value; (A) Even Distribution, (B) Bursty Distribution.

For a better cognition model, two psychoacoustic results [Zwicker and Fastl, 1990] have been incorporated: (1) the hearing system integrates the sound intensity over a period of 200 ms, and (2) premasking is relatively short, while postmasking can last longer than premasking. According to these psychoacoustic results, it may not be appropriate to directly use the distortion value obtained

using 40 ms frames. So, a new cognition model is developed incorporating these psychoacoustic results.

Several terms are defined for a new cognition model. A cognizable segment is defined as a set of consecutive frames corresponding to approximately 200 ms. A cognizable unit (v) is defined as the number of frames in a cognizable segment. Perceptual distortion ($P(j)$) is defined as a maximum distortion value over a cognizable segment. Postmasking distortion ($Q(j)$) is defined as the amount of the previous cognizable distortion masking the current perceptual distortion. Cognizable distortion ($C(j)$) is defined as the largest value between the current perceptual distortion and the postmasking distortion. Then, the final distortion value of test speech utterance is the average over the cognizable distortions. The cognizable distortion as measured by using postmasking is assumed to contribute to listeners' response on speech quality even when there is no distortion at the current perceptual distortion.

The following equations formally define the final distortion value, *EMBSD*.

$$EMBSD = \frac{1}{U}\sum_{j=1}^{U} C(j) \tag{34}$$

$$C(j) = \max\left(P(j), Q(j)\right) \tag{35}$$

$$P(j) = \max\begin{bmatrix} MBSD(v(j-1)+1), MBSD(v(j-1)+2), \\ ..., MBSD(v(j-1)+v) \end{bmatrix} \qquad (36)$$

where *C(j)*, *P(j)*, and *Q(j)* are the cognizable distortion, the perceptual distortion, and the postmasking distortion of the *j*-th cognizable segment, respectively. *U* is the total number of cognizable segments and *v* is the cognizable unit. *MBSD(i)* is the same as defined in Eq. (32).

As an initial attempt to model the postmasking effect for the calculation of postmasking distortion, λ% of the previous cognizable distortion is assumed to contribute postmasking effect on the current cognizable segment. Let us call λ the postmasking factor. So, the postmasking distortion (*Q(j)*) of the *j*-th cognizable segment is defined as

$$Q(j) = \frac{l}{100} C(j-1) \qquad (37)$$

In order to adopt the new cognition model, the cognizable unit (*v*) and the postmasking factor (λ) must be determined. Using TDMA data, the best values of these two parameters were searched as follows. First, the cognizable unit was varied from 1 to 20 frames for a fixed postmasking factor of 80.

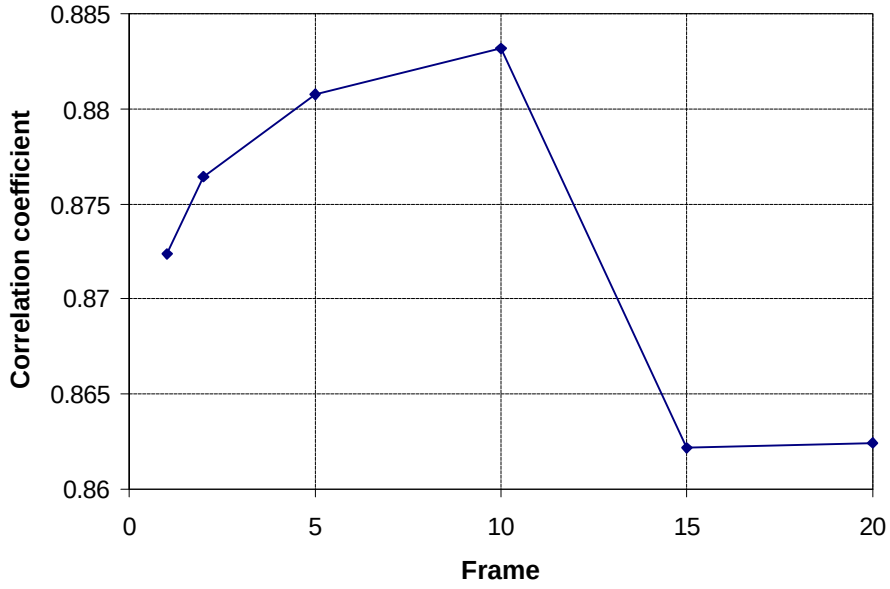


Figure 17. Performance of the MBSD With a new Cognition Model as a Function of Cognizable Unit for the Postmasking Factor of 80.

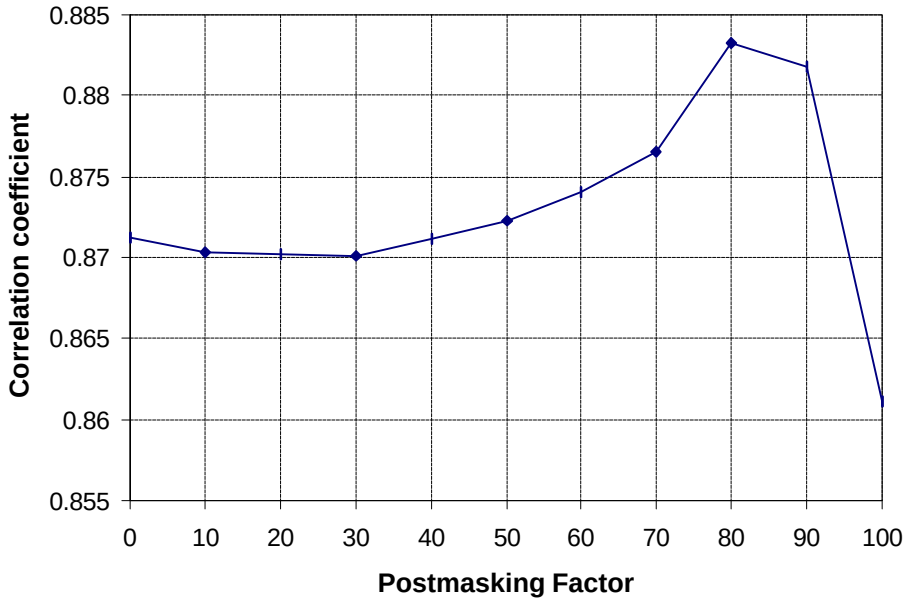


Figure 18. Performance of the MBSD With a new Cognition Model as a Function of Postmasking Factor for the Cognizable Unit of 10 Frames.

As shown in Figure 17, the best result occurs at the cognizable unit of 10 frames. Since the measure used the frame length of 320 samples (corresponding to 40ms) with 50% overlap, the cognizable unit of 10 frames approximately corresponds to 200 ms, which is consistent with the psychoacoustic result that the hearing system integrates the sound intensity over a period of 200 ms [Zwicker and Fastl, 1990].

In order to determine the postmasking factor, similar experiments were performed. The postmasking factor was varied from 0 to 100 for the cognizable unit of 10 frames. As shown in Figure 18, the best result occurs at the postmasking factor of 80.

According to the results of these experiments, a new cognition model with a cognizable unit of 10 frames and a postmasking factor of 80 has been adopted to improve the MBSD.

CHAPTER 6

ENHANCED MODIFIED BARK SPECTRAL DISTORTION (EMBSD)

The EMBSD is an enhancement of the MBSD measure in which some procedures of the MBSD have been modified and a new cognition model has been used. Some of the basic aspects of the MBSD algorithm have been examined using TDMA data, as described in Chapter 5. The MBSD was modified using information obtained from the experiments with TDMA data, the result is the EMBSD. These modifications are summarized as follows:

(1) using only the first 15 loudness components to calculate loudness difference, as shown in Eq. (32),

(2) normalizing loudness vectors before calculating loudness difference, as shown in Eq. (33),

(3) deleting the spreading function in the calculation of noise masking threshold,

(4) adopting a new cognition model based on postmasking effects, as described in Section 5.5.

The block diagram of the EMBSD measure is shown in Figure 19. The EMBSD computes the distortion frame-by-frame, with the frame length of 320 samples overlapping by a half frame. Each frame is weighted by a Hanning window. Here, *x(n)* and *y(n)* denote the *n-th* frame of the original and distorted

speech, respectively. $L_x(n)$ and $L_y(n)$ are the normalized loudness vectors of the *n-th* frame of the original and distorted speech, respectively. $D_{xy}(n)$ is the loudness difference between $L_x(n)$ and $L_y(n)$, and $NMT(n)$ is the noise masking threshold calculated from the original speech without the spreading function. The new cognitive model uses the distortion value of the *n*-th frame, $MBSD(n)$ to calculate the estimated distortion.

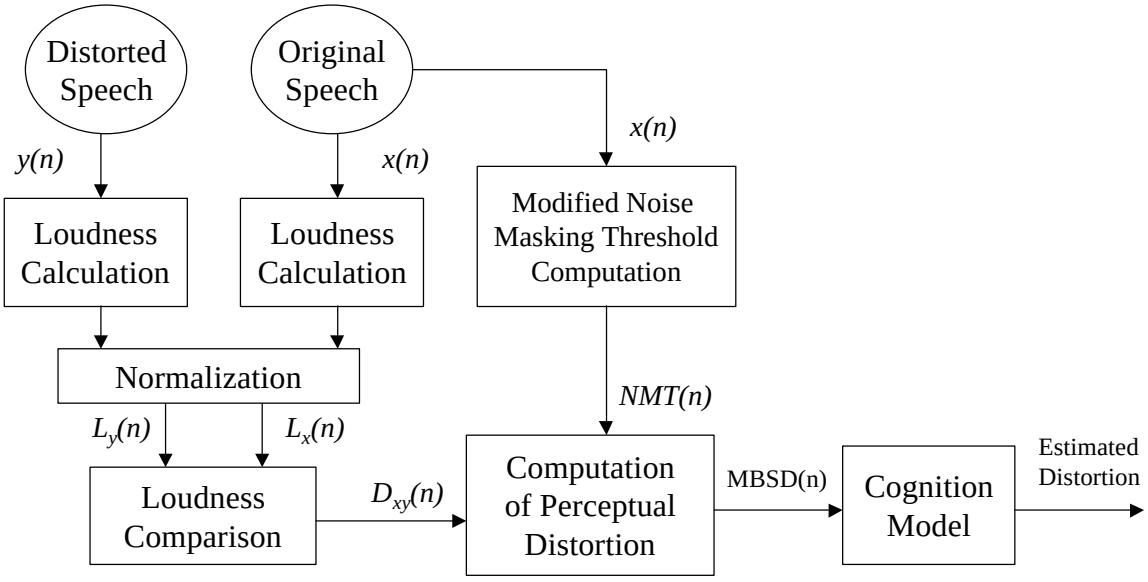


Figure 19. Block Diagram of the EMBSD Measure.

The loudness calculation of a frame is the same as that of the MBSD, as described in Section 5.1. The loudness vector of distorted speech is normalized before computing the loudness difference, as described in Eq. (32). The noise masking threshold is computed with original speech without the spreading function. The perceptual distortion is computed using the first 15 loudness components where the loudness difference is greater than the noise masking threshold. Finally, a new cognitive model is used to calculate the estimated distortion of the distorted speech. The actual EMBSD program written in C code is given in Appendix B.

CHAPTER 7

PERFORMANCE OF THE EMBSD MEASURE

The performance of the EMBSD measure has been evaluated with three different sets of speech data, and compared with the MBSD, ITU-T Recommendation P.861, and the MNB measures.

The first speech data set (Speech Data I) was generated by Lucent Technologies. The distortion conditions in this speech data were coding distortions. There were five Modulated Noise Reference Unit (MNRU) conditions and nine different types of speech codecs such as ADPCM, GSM, IS-54, FS-1016, LD-CELP, CELP, and so on. MNRU is the condition of Gaussian noise where the power levels of noise is varied according to the power levels of the speech signal to keep a constant SNR over the entire speech utterance.

The second speech data set (Speech Data II) was generated by AT&T. The data was collected from real network environments. All data were recorded over in-service TDMA and AMPS RF links in 1994 in a mobile environment. There were forty-nine different types of distortions encountered in real network environments with seven MNRU conditions.

The third speech data set (Speech Data III) was generated by Nortel Networks. This speech data contains a relatively wide range of distortion conditions such as MNRUs, various codecs, various tandeming cases, temporal

shifting and clipping, bit errors, frame erasures, and amplitude variations [Thorpe and Yang, 1999]. Some distortion conditions, such as temporal shifting and clipping, and amplitude variations, are not usually used for the evaluation of objective quality measures. This speech data has subjective ratings of both MOS and DMOS.

The performance of the objective quality measures has been evaluated using both the correlation coefficient (r) and the standard error of the estimates (SEE) (as discussed in section 3.2 and 3.3).

7.1. Performance of the EMBSD with Speech Data I

Figure 20 shows the scatterplots of P.861, MNB2, the MBSD, and the EMBSD with Speech Data I. Each point indicates the results of the average of the various objective quality estimates and the associated MOS for each condition. Because objective quality measures generate a distortion number, the smaller the result of objective measures, the higher the MOS score. As shown in Figure 20, the range of the distortion values of the various objective quality measures is different and some objective estimates are not linearly related to the MOS scores. Therefore, the results of the objective quality measures were transformed to have

a linear relation with the MOS scores using the regression curve. Figure 21 shows the scatterplots of the transformed objective estimates against the MOS scores.

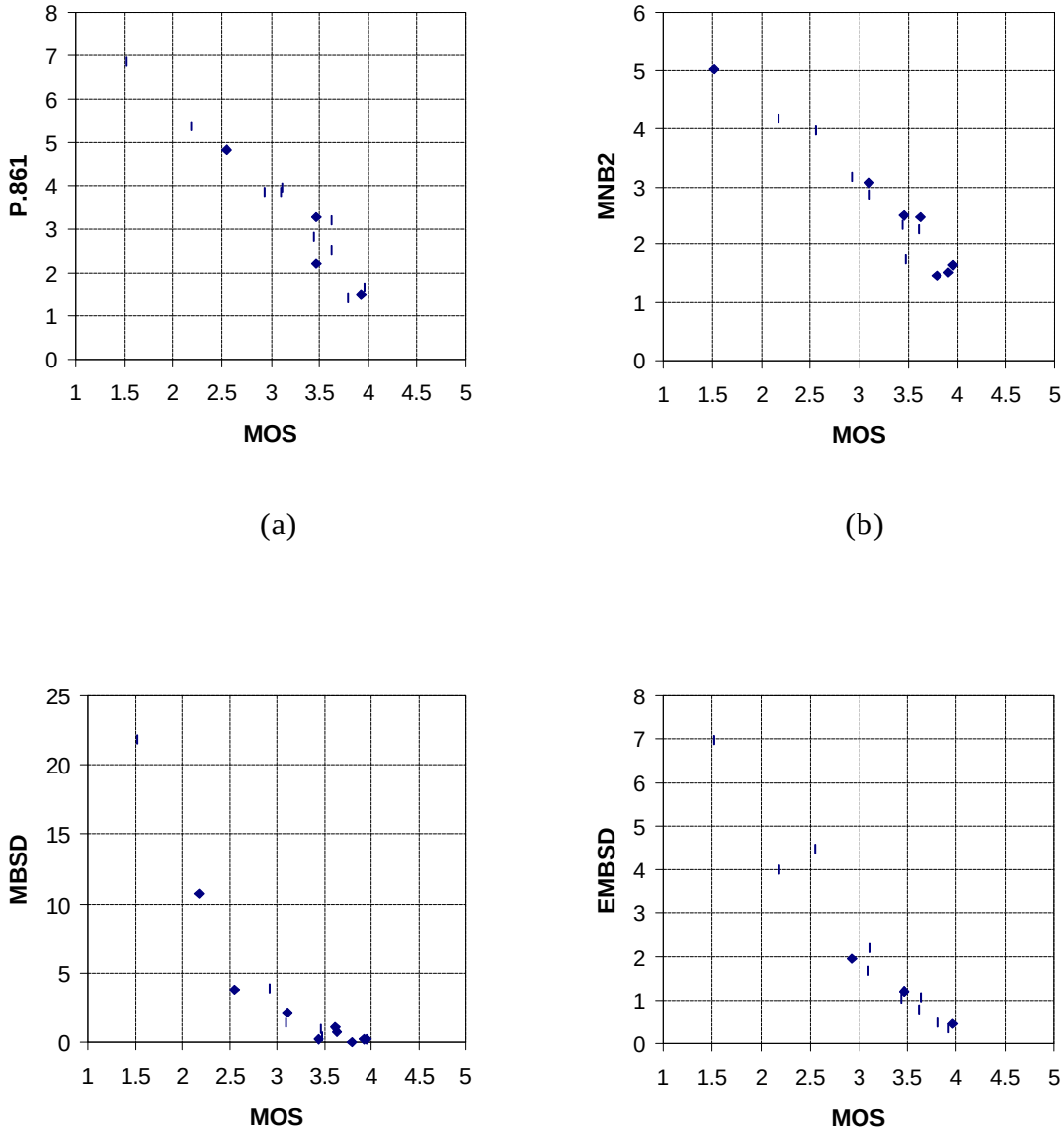
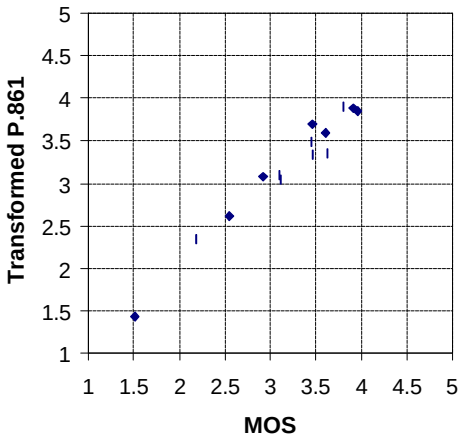
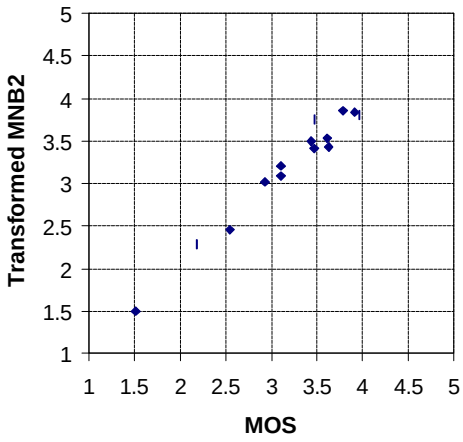


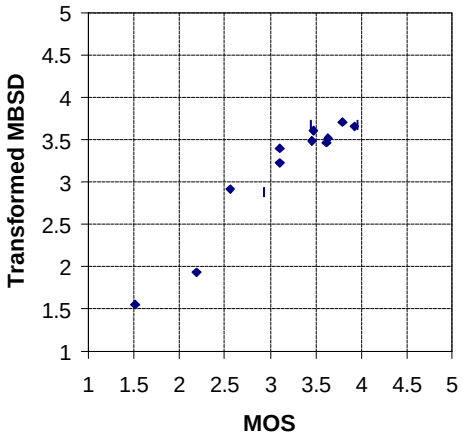
Figure 20. Objective Measures of P.861, MNB2, MBSD, and EMBSD Versus MOS Scores for Speech Data I.



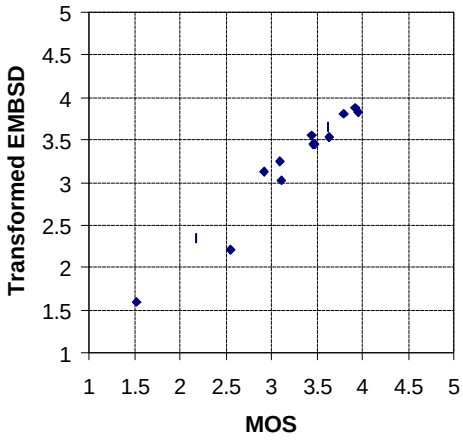
(a)



(b)

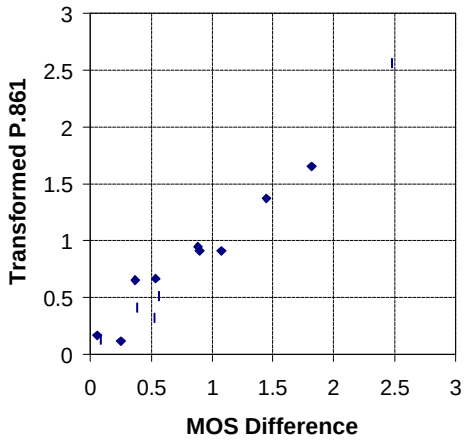


(c)

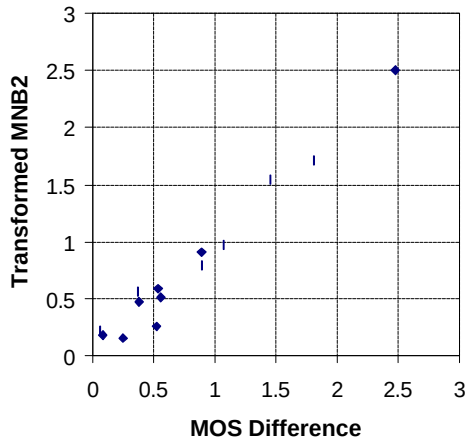


(d)

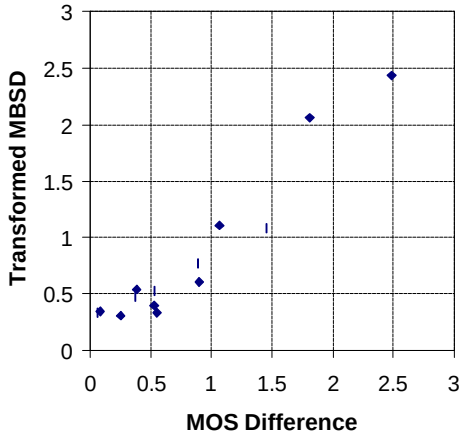
Figure 21. Transformed Objective Estimates of P.861, MNB2, MBSD, and EMBSD Versus MOS Scores for Speech Data I.



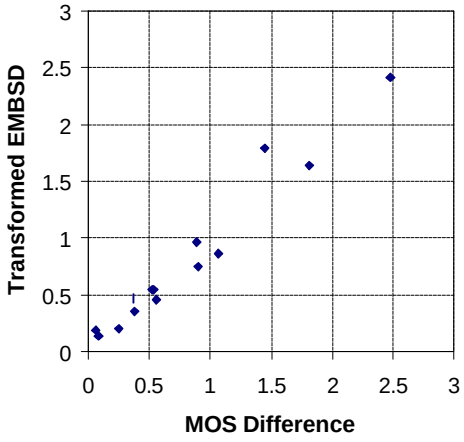
(a)



(b)



(c)



(d)

Figure 22. Transformed Objective Estimates of P.861, MNB2, MBSD, and EMBSD Versus MOS Difference for Speech Data I.

Since current objective quality measures estimate the speech quality by comparing the distorted speech to the original speech, which is similar to DMOS test, the performance parameters of these measures were also calculated against the MOS difference (MOS of original speech – MOS of distorted speech) [Yang et al., 1998], because the DMOS scores were not available. Figure 22 shows the scatterplots of the transformed objective estimates against the MOS difference.

The performance parameters of the objective quality measures against subjective ratings for both the MOS scores and the MOS difference were calculated using the transformed objective estimates. Table 8 summarizes these results.

Table 8. Correlation Coefficients and SEE of Objective Quality Measures With Speech Data I

	Correlation Coefficient		SEE	
	MOS	MOS Difference	MOS	MOS Difference
MBSD	0.95	0.96	0.22	0.21
P.861	0.98	0.98	0.14	0.14
MNB2	0.98	0.98	0.13	0.13
EMBSD	0.98	0.98	0.15	0.15

The correlation coefficients for P.861, MNB2, and EMBSD were the same. These measures account for approximately 96% of the variance in the subjective ratings.

The SEE values were slightly different, but their small differences are not statistically significant. The EMBSD showed some improvement over the MBSD with Speech Data I and the performance of the EMBSD is comparable to those of P.861 and MNB2 for Speech Data I.

7.2. Performance of the EMBSD with Speech Data II

Figure 23 shows the scatterplots of the MBSD, EMBSD, and P.861 with Speech Data II. As with Speech Data I, the results of the objective quality measures were transformed to have a linear relation with the MOS scores using the regression curve. Figure 24 shows the scatterplots of the transformed objective estimates against the MOS scores. Inspection of the scatterplots shows that correlations of the objective quality measures with Speech Data II are lower than those with Speech Data I. Also, it is clear that the EMBSD showed better correlation than the MBSD. Since the DMOS scores were not available for Speech Data II, the analysis against the DMOS scores was not performed. The analysis against the MOS difference could not be performed because the MOS scores of the original speech samples were not available for Speech Data II.

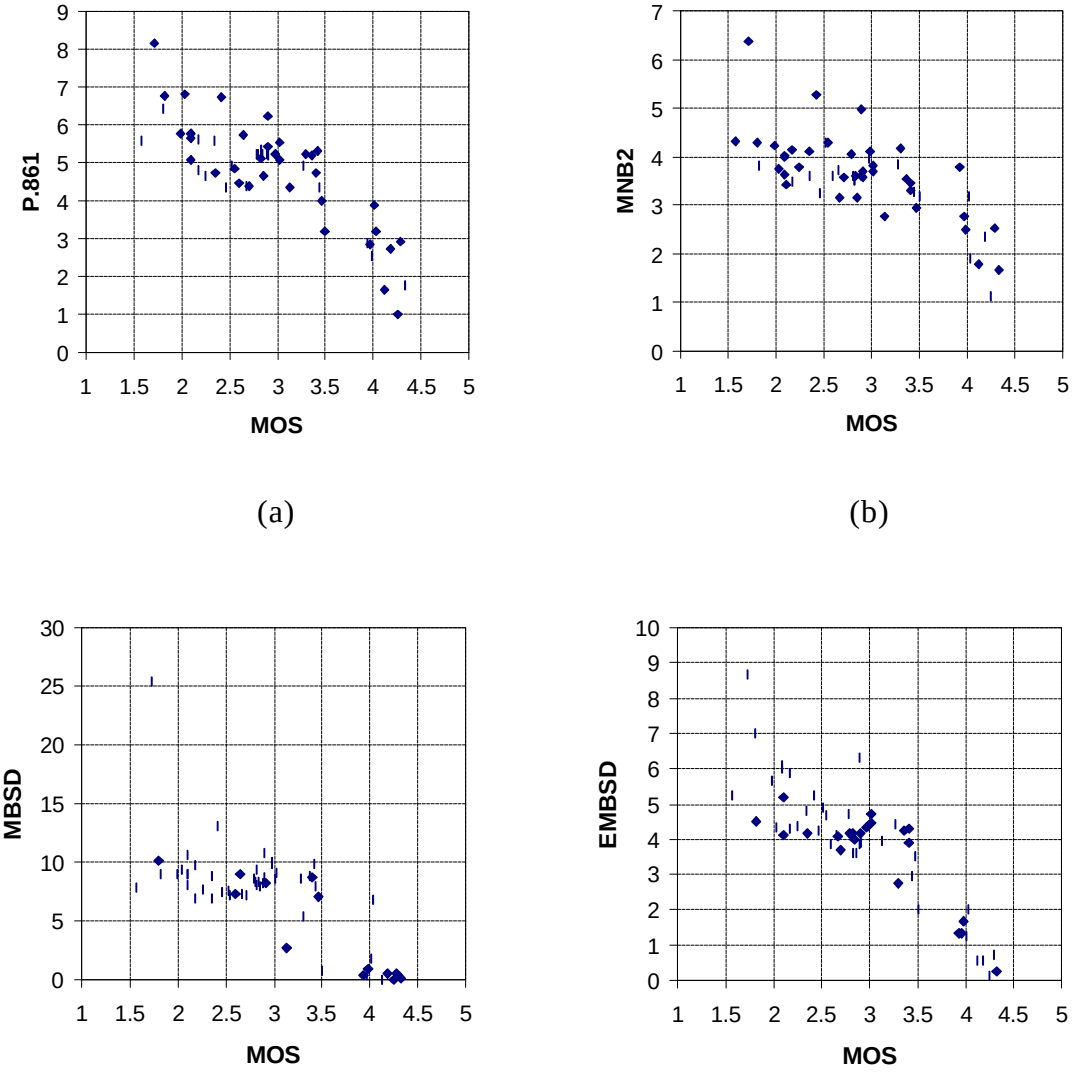


Figure 23. Objective Measures of P.861, MNB2, MBSD, and EMBSD Versus MOS scores for Speech Data II.

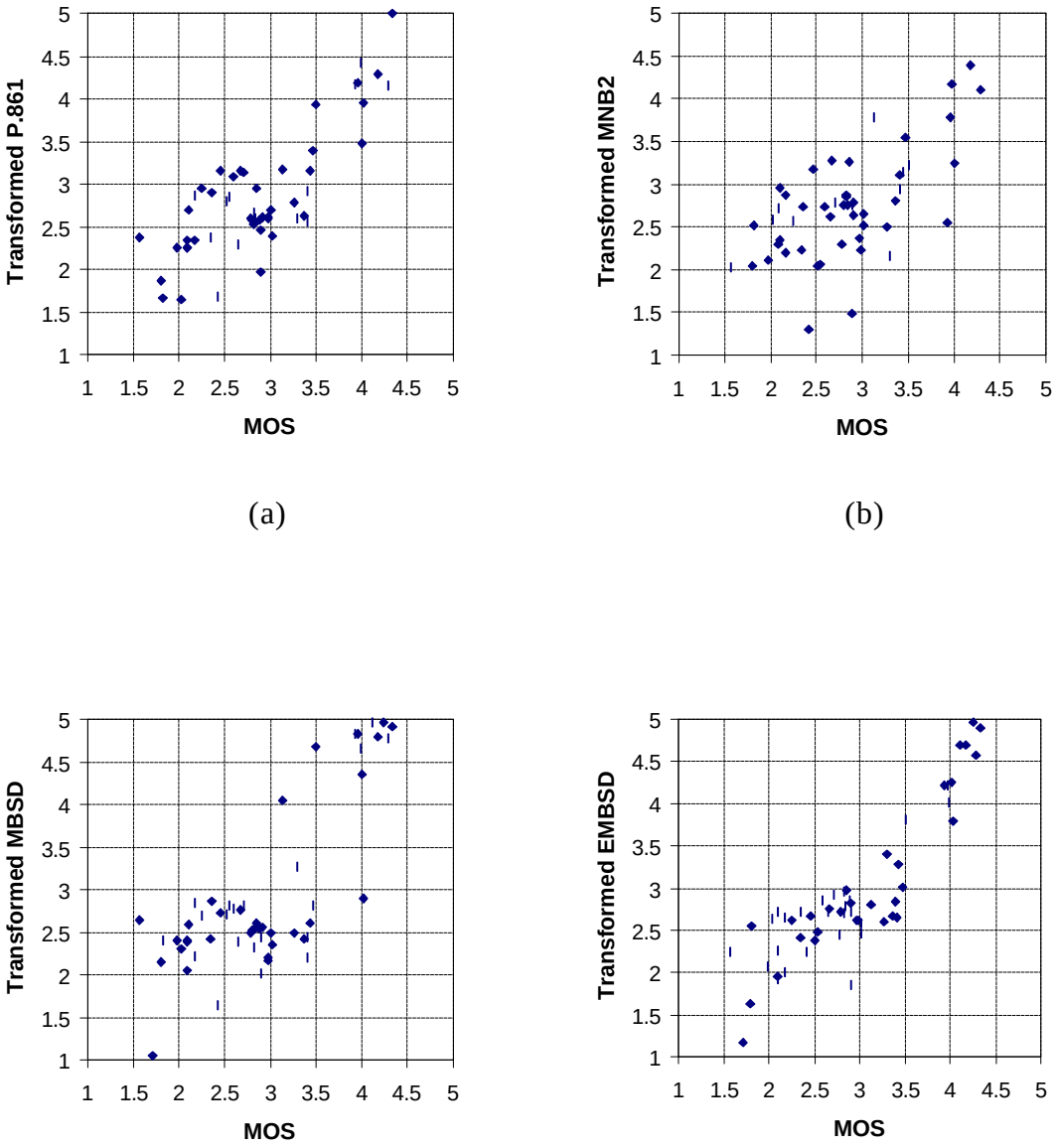


Figure 24. Transformed Objective Estimates of P.861, MNB2, MBSD, and EMBSD Versus MOS Scores for Speech Data II.

The performance parameters of the objective quality measures against subjective ratings of the MOS scores were calculated using the transformed objective estimates. Table 9 summarizes these results.

Table 9. Correlation Coefficients and SEE of Objective Quality Measures Versus MOS With Speech Data II

	Correlation Coefficient	SEE
P.861	0.83	0.51
MNB2	0.74	0.67
MBSD	0.76	0.61
EMBSD	0.87	0.41

The correlation results of each objective quality measure for Speech Data II were much lower than those for Speech Data I. This result reflects the fact that the performance of these measures depends on the type of distortion. The performance of the EMBSD shows clear improvement over the MBSD for Speech Data II. The correlation coefficient of the EMBSD is nominally higher than that of P.861. The EMBSD value accounts for around 76% of the variance in the subjective MOS scores. The P.861 value accounts for about 69% of the variance in the subjective MOS scores. The SEE value of the EMBSD is smaller than that of P.861 by around 0.1. Speech Data II was one of the most challenging data sets for objective quality measures. Since Speech Data II were recorded in real network

environments, the performance of objective quality measures for Speech Data II can be considered as the accuracy of these measures when they are actually applied in the real network applications. Although the performance of the EMBSD was not still satisfactory for real network applications, it certainly showed promising results for Speech Data II.

7.3. Performance of the EMBSD Measure with Speech Data III

The distortion conditions of Speech Data III can be classified into seven groups: MNRUs (Group 1), coders on clean channel (Group 2), tandem cases (Group 3), temporal shifting and front-end clipping (Group 4), bit errors (Group 5), frame erasures (Group 6), and level variations (Group 7).

Group 1 includes MNRU conditions with a range of 5 dB to 35 dB. In Group 2, various coding distortions are included. Speech compression codecs were chosen based on contrasting algorithms, and covering a wide range of bit rates. The bit rates of these codecs range from 2.4 Kb/s to 64 Kb/s. Group 3 covers some plausible tandeming cases that might be encountered in GSM, TDMA, and CDMA networks. In tandeming cases, several codecs are processed in series. Group 4 contains temporal shifting (which may occur due to variable jitter buffers in voice-over-IP networks) and front-end clipping (which may occur

where voice activated switching or discontinuous transmission features are used). In Group 5, codecs of GSM and TDMA networks are subjected to bit error rates of 1, 2, or 3%. Group 6 contains frame erasures at similar rates (1, 2, or 3%) for codecs in wireless networks as well as voice over IP. These conditions are included to determine the performance of objective measures on the channel impairments of different types of networks. In Group 7, speech levels were varied in the original material, which was then processed through an automatic gain control (AGC). Some conditions in Group 7 also have front-end clipping.

The test condition groups can be divided into two types: (1) target conditions — distortions usually intended to be evaluated using objective quality measures (Group 1, 2, 3, 5, and 6), and (2) non-target conditions — distortions not usually intended to be evaluated using these measures (Group 4 and 7). The condition groups were broken up into these two types because some of the test conditions (the non-target conditions) are outside the set of distortions that objective measures are generally intended to address. These conditions were included to investigate the generalizability of the measures to common network impairments and artifacts. The performance of the measures examined is evaluated against all the conditions, as well as against each type (target and non-target) separately.

Table 10 summarizes the correlation coefficients of various objective quality measures against overall conditions, as well as against target conditions

[Thorpe and Yang, 1999]. The correlation coefficients between the objective estimates and the subjective scores were calculated after transforming the objective estimates with the regression curve obtained from the scatterplot of target conditions. The name of each measure has not been released because of the project agreement. These objective quality measures appeared to correlate better with DMOS than with MOS. This result may follow from the procedural difference between current objective speech quality measures and MOS test.

Table 10. Correlation Coefficients of Various Objective Quality Measures With Speech Data III [Thorpe and Yang, 1999]

Measure	Overall Conditions (60)		Target conditions (49)	
	MOS	DMOS	MOS	DMOS
A	0.87	0.97	0.88	0.95
B	0.85	0.96	0.86	0.94
C	0.56	0.65	0.89	0.94
D	0.86	0.92	0.83	0.87
E	0.90	0.95	0.87	0.96
F	0.86	0.94	0.84	0.91
MBSD	0.24	0.29	0.76	0.82
EMBSD	0.54	0.65	0.89	0.94

The analysis results show that the EMBSD estimates are well correlated with subjective DMOS ratings for the target conditions, but appear to have poor correlation for the overall case. The EMBSD value of the target conditions

accounts for about 79% (for MOS) and 88% (for DMOS) of the variance in the subjective ratings. Correlations for the overall case were much lower and the EMBSD was able to predict only about 30~40% of the variation in the actual listener ratings.

Figure 25 shows the scatterplots of the transformed EMBSD against MOS and DMOS. Inspection of the scatterplots shows that the poor performance in the overall case is accounted for by the non-target conditions. The MOS estimates of the temporal shifting and clipping conditions (Group 4) were widely spread, while being rated high by the listeners. Since the EMBSD assumes that the distorted speech is synchronized with the original speech, the EMBSD estimates of Group 4 are meaningless because the measure has compared the wrong frames to estimate speech quality.

Also, the AGC conditions (Group 7) were given high MOS estimates, while being rated lower by the listeners. Most objective quality measures showed results similar to that for Group 7. This result is caused by the underlying assumption of current objective speech quality measures, that is, the quality of input speech is always excellent. In order to improve performance of objective quality measures for such conditions, a new model would be necessary. If only the target conditions are considered, then the EMBSD is an effective objective quality measure.

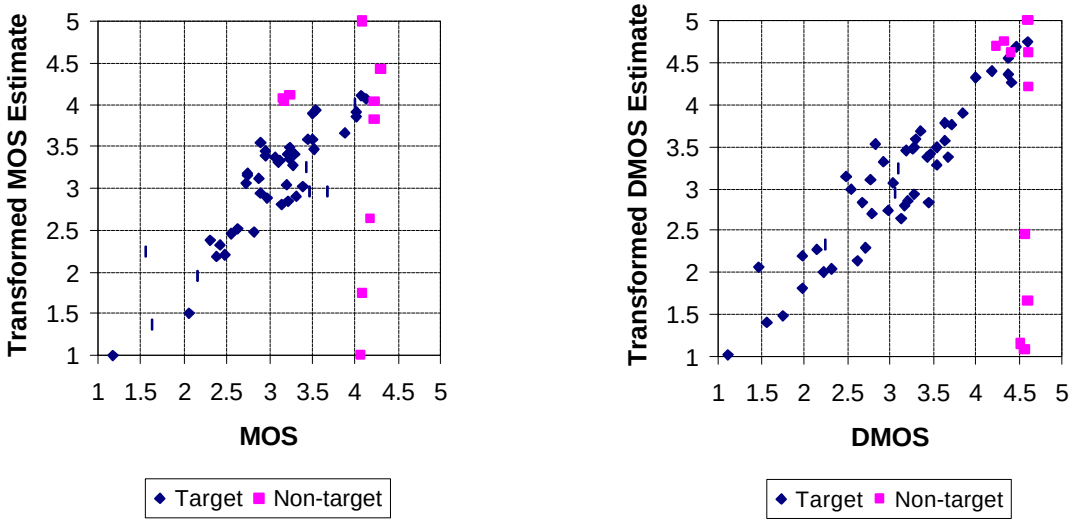


Figure 25. Transformed Objective Estimates of EMBSD Versus MOS and DMOS for Speech Data III.

The results of Table 10 clearly show that current objective quality measures are actually performing better at predicting the DMOS scores rather than the MOS scores because all of the measures showed better correlation with DMOS than with MOS. This is not a surprising result because current objective quality measures estimate subjective scores by comparing the distorted speech to the original speech, which is analogous to DMOS test.

Table 11 shows the SEE values for overall, target, and non-target conditions. The number in the parenthesis indicates the number of conditions. Note that the SEE value indicates how much the estimates values deviate from

the actual values. So, the smaller the SEE, the better the performance of the objective quality measure. The SEE measure shows a similar tendency in performance as shown for correlation coefficients. Note that the SEE values of the EMBSD for the non-target cases are high (the corresponding result for the correlation analysis is not available because of the small number of data points). This result indicates that the EMBSD is not yet prepared for the non-target conditions. However, the EMBSD presently is one of the best predictors of subjective ratings for the target conditions in Speech Data III among the measures evaluated. Also, the EMBSD shows better performance for both target and non-target conditions than the MBSD.

Table 11. Standard Error of the Estimates of Various Objective Quality Measures With Speech Data III [Thorpe and Yang, 1999]

Measure	Overall (60)		Target (49)		Non-target (11)	
	MOS	DMOS	MOS	DMOS	MOS	DMOS
A	0.44	0.26	0.36	0.27	0.76	0.23
B	0.50	0.29	0.41	0.29	0.87	0.33
C	0.74	0.81	0.32	0.28	1.72	1.97
D	0.48	0.46	0.43	0.46	0.73	0.49
E	0.43	0.30	0.36	0.24	0.70	0.53
F	0.43	0.31	0.41	0.35	0.56	0.09
MBSD	1.03	1.19	0.48	0.49	2.36	2.80
EMBSD	0.78	0.85	0.32	0.31	1.83	2.04

Table 12 shows the SEE for three target condition groups (Group 1, 2, and 3). The EMBSD measure showed better performance for Group 1 and 3 against both MOS and DMOS among these measures. The prediction errors of the EMBSD for Group 2 were large compared to the results with other condition groups.

Table 12. Standard Error of the Estimates of Various Objective Quality Measures for Target Condition Groups (Group 1, 2, and 3) of Speech Data III [Thorpe and Yang, 1999]

Measure	Group 1 (7)		Group 2 (12)		Group 3 (12)	
	MOS	DMOS	MOS	DMOS	MOS	DMOS
A	0.44	0.32	0.34	0.27	0.51	0.30
B	0.43	0.20	0.43	0.36	0.58	0.37
C	0.48	0.28	0.33	0.33	0.38	0.24
D	0.44	0.45	0.57	0.56	0.41	0.47
E	0.48	0.25	0.45	0.27	0.43	0.29
F	0.37	0.17	0.38	0.31	0.59	0.53
MBSD	0.37	0.46	0.66	0.77	0.62	0.47
EMBSD	0.27	0.29	0.43	0.45	0.36	0.24

Table 13 shows the SEE for other target condition groups (Groups 5 and 6). The EMBSD measure showed relatively small prediction errors for Groups 5 and 6 against both MOS and DMOS as compared to all the other measures. According to Table 12 and Table 13, the EMBSD measure showed relatively

promising results over other measures for the target conditions except probably Group 2.

Table 13. Standard Error of the Estimates of Various Objective Quality Measures for Target Condition Groups (Group 5 and 6) of Speech Data III [Thorpe and Yang, 1999]

Measure	Group 5 (5)		Group 6 (13)	
	MOS	DMOS	MOS	DMOS
A	0.30	0.33	0.31	0.29
B	0.35	0.34	0.33	0.26
C	0.37	0.49	0.29	0.26
D	0.60	0.76	0.41	0.42
E	0.27	0.27	0.28	0.25
F	0.41	0.38	0.40	0.35
MBSD	0.26	0.27	0.39	0.41
EMBSD	0.25	0.34	0.31	0.32

Table 14 shows the SEE for the non-target condition groups (Groups 4 and 7). The SEE values of the EMBSD for Group 4 were much higher against both MOS and DMOS because the EMBSD did not take time alignments between the sentences into account. The performance of the EMBSD on Group 4 could be improved by adopting dynamic time alignment algorithms. Most measures did not consider the conditions of Group 7, where original speech samples were distorted. Since there is a possibility that the output speech of a voice processing

system sounds better than the input speech, the objective measures must take into consideration this kind of distortion, in the future.

Table 14. Standard Error of the Estimates of Various Objective Quality Measures for Non-Target Condition Groups (Group 4 and 7) of Speech Data III [Thorpe and Yang, 1999]

Measure	Group 4 (8)		Group 7 (3)	
	MOS	DMOS	MOS	DMOS
A	0.32	0.11	2.15	0.62
B	0.44	0.22	2.38	0.82
C	1.90	2.39	2.25	0.84
D	0.56	0.47	1.69	0.94
E	0.80	0.45	0.76	1.14
F	0.18	0.10	1.64	0.14
MBSD	2.89	3.37	0.55	1.51
EMBSD	2.16	2.49	1.52	0.63

CHAPTER 8

FUTURE RESEARCH

There are several possible areas of research related to the EMBSD objective speech quality measure.

First, the EMBSD measure regards the loudness difference above the noise masking threshold as audible distortion, and does not take into consideration the relative significance of these components. It is well known in the speech coding community that the spectral peaks (formants) are more important than the spectral valleys. Therefore, if a perceptually relevant weighting scheme is applied to the loudness difference for spectral peaks and valleys above the noise masking threshold, the EMBSD might be further improved.

Second, the EMBSD measure has been developed based on the assumption that both the distorted and the original speech are time-aligned. In real applications, it is rare to have both the distorted and the original speech synchronized. Also, variable delays between the consecutive non-silence segments are common in current packet networks. For instance, such variable delays occur due to variable jitter buffers on voice transmission over IP networks. Without proper time alignment pre-processing, the result of objective quality measures would be meaningless. Therefore, a reliable and effective time alignment algorithm should be used as pre-processing.

Third, the EMBSD measure showed relatively good performance over several target conditions according to the experiments with Speech Data III. Among these target conditions, the EMBSD showed relatively larger prediction error for Group 2 (codecs), as shown in Figure 26.

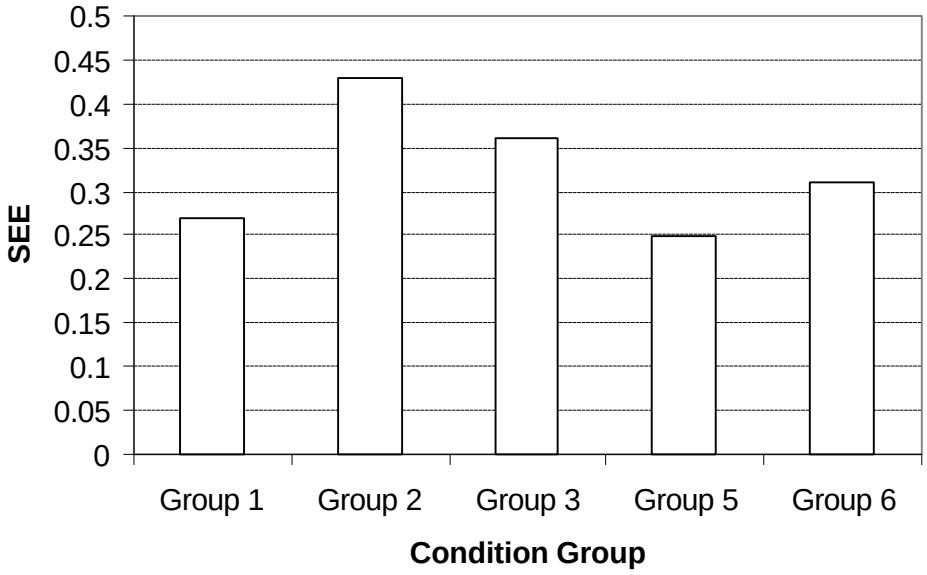


Figure 26. Performance of the EMBSD Against MOS
for the Target Conditions of Speech Data III.

It could be worthwhile to examine the coding distortion types that the EMBSD did not perform well. After identifying these coding distortions, the EMBSD could be further improved by reducing the prediction errors on these

coding distortions while ensuring that any changes will have no adverse affects on the performance of the EMBSD with other distortions.

Finally, the EMBSD did not consider the distortion conditions where original speech samples are distorted. Since there is a possibility that the output speech of a voice processing system sounds better than the input speech, the EMBSD measure must take into consideration this kind of distortion in the future.

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APPENDIX A

MATLAB PROGRAM OF MBSD

```
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%                                                                                 %
%                MODIFIED BARK SPECRAL DISTORTION MEASURE                         %
%                                                                                 %
%                FILE NAME: MBSD.M                                                %
%                DEVELOPER: WONHO YANG                                            %
%                                                                                 %
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

nlength = 320;          % FRAME SIZE OF 20ms IN SAMPLES
N = 1024;               % FFT LENGTH
flag1 = 0;              % INITIALIZATION FOR ABSOLUTE THRESHOLD
w = hanning(nlength);   % HANNING WINDOW

filename = 'f1.mat';
processed = 0;          % NONSILENCE FRAMES PROCESSED
Bf = 1:18;              % CRITICAL BANDS
mbsd = 0;               % MBSD DISTORTION OF A FRAME

eval(['load c:\spdat\orig\',filename])
% READ ORIGINAL FILE (filename : "c:\spdat\orig\f1.mat")
original = samples';          % ORIGINAL SPEECH
clear samples

eval(['load c:\spdat\dist\' filename])
% READ DISTORTED FILE (filename : "c:\spdat\dist\f1.mat")
distorted = samples';   % DISTORTED SPEECH
clear samples

if length(original) < length(distorted)
      LL = length(original);  % LENGTH OF SPEECH SAMPLES
else
      LL = length(distorted);
end

b1 = 1;           % BEGINNING OF A FRAME
b2 = nlength;     % END OF A FRAME

while b2 < LL

      % FRAMING
      x = original(b1:b2);    % ORIGINAL FRAME
      z = distorted(b1:b2);   % DISTORTED FRAME

      % CHECK FOR SILENCE/NON-SILENCE
      if ( sum(x.^2) < 1000 )
            flag = 0;   % SILENCE FRAME
      else
```

```
      flag = 1;   % NON-SILENCE FRAME
end

if flag == 1      % PROCESS NON-SILENCE FRAMES

      % HANNING WINDOWING
      xw = w' .* x;
      zw = w' .* z;

      % POWER SPECTRUM
      [XX, freq] = fft_n01(N, xw);
      [ZZ, freq] = fft_n01(N, zw);

      % BARK SPECTRUM
      [B_XX, bark] = bk_frq02(Bf, freq, XX);
      [B_ZZ, bark] = bk_frq02(Bf, freq, ZZ);

      % ABSOLUTE HEARING THRESHOLD
      if flag1 == 0
            Abs_thresh = thrshld2(freq,bark);
            flag1 = 1;
      end

      % SPREAD BARK SPECTRUM
      C_XX = spread2(Bf, B_XX);
      C_ZZ = spread2(Bf, B_ZZ);

      % CONVERTING SPREAD BARK SPECTRUM INTO PHON SCALE
      P_XX = dbtophon(C_XX);
      P_ZZ = dbtophon(C_ZZ);

      % SPECTAL FLATNESS MEASURE
      alpha = sfm1(XX);

      % Noise Masking Threshold
      norm = XX(1);
      Offset_XX = thresh2(Bf, alpha, 10*log10(C_XX), norm);
      Noise_Th = last_th(Bf, Offset_XX, Abs_thresh);
      P_NT = dbtophon(10.^(Noise_Th/10));

      % CONVERTING INTO LOUDNESS
      S_XX = phtosn(P_XX);
      S_ZZ = phtosn(P_ZZ);
      S_NT = phtosn(P_NT);

      % CALCULATING THE INDICATOR OF PERCEPTIBLE DISTORTION
      Mask = mark(abs(S_ZZ-S_XX), S_NT);

      ttm3 = ediff2(S_XX, S_ZZ, Mask, 1); % MBSD FOR A FRAME

      mbsd = mbsd + ttm3;     % SUM OF MBSD VALUES

      processed = processed + 1;    % NUMBER OF FRAMES PROCESSED
```

```
      end   % END OF IF

      b1 = b1 + nlength/2;    % 50% OF OVERLAPPING
      b2 = b2 + nlength/2;    % 50% OF OVERLAPPING

end   % END OF WHILE

MBSD = mbsd/processed   % MBSD VALUE FOR A DISTORTED SPEECH

% END OF MBSD.M



%
% FILE NAME: FFT_N01.M
%
function [XX, freq] = fft_n01 (N, xwv)
% PERFORMS AN N POINT FFT

X = fft (xwv', N);
XX = X .* conj(X) / N;
freq = 4000 * (0:((N/2)-1)) / (N/2);
XX (((N/2)+1):N) = [ ];
XX (2:(N/2)) = 2 * XX (2:(N/2));

% END OF FFT_N01.M



%
% FILE NAME: BK_FRQ02.M
%
function [B_XX, bark] = bk_frq02(Bf, freq, XX)
% COMPUTES CRITICAL BANDS IN THE BARK SPECTRUM

% CRITICAL BANDS FROM "FOUNDATION OF MODERN AUDITORY THEORY"
bark(1) = 0;
bark(2) = 100;
bark(3) = 200;
bark(4) = 300;
bark(5) = 400;
bark(6) = 510;
bark(7) = 630;
bark(8) = 770;
bark(9) = 920;
bark(10) = 1080;
bark(11) = 1270;
bark(12) = 1480;
bark(13) = 1720;
bark(14) = 2000;
bark(15) = 2320;
bark(16) = 2700;
bark(17) = 3150;
bark(18) = 3700;
```

```
bark(19) = 4400;

for i=2:19
B_XX(i-1)=sum(XX(bark(i-1)<=freq & freq<bark(i)));
end

% END OF BK_FRQ02.M



%
% FILE NAME: THRSHLD2.M
%
function Abs_Thr = thrshld2(freq, bark)
% ESTIMATE THE THRESHOLD OF HEARING IN dB BY THE FORMULA OF Terhardt
%
% thrshld(f) = { 3.64(f/1000)^(-0.8) - 6.5exp[-0.6(f/1000 - 3.3)^2]
%            + 0.001(f/1000)^4 }
%
% THIS FORMULA PRODUCES THRESHOLD OF HEARING IN dB
% REFERENCE: Terhardt, E., Stoll, G. and Seewann, M, "Algorithm for
%     extraction of pitch and pitch salience from complex tone
%     tonal signals", J. Acoust. Soc. Am., vol. 71(3), Mar., 1982

f1 = freq(2:length(freq))/1000;
L(1) = 0;
L(2:length(freq)) = 3.64./(f1.^0.8) - 6.5*exp(-0.6*(f1-3.3).^2) +
                        0.001*f1.^4;

L1 = L(2:length(freq));
for i = 2:19
      B_XX = L1(bark(i-1)<=freq(2:length(freq)) & freq(2:length(freq))
             <bark(i));
      if B_XX ~= []
         Abs_Thr(i-1) = mean(B_XX);
      else
         Abs_Thr(i-1) = 0;
      end
end

% END OF THRSHLD2.M



%
% FILE NAME: SPREAD2.M
%
function C = spread2(Bf, Bi)
% COMPUTES THE SPREAD CRITICAL BAND SPECTRUM, USING THE SPREADING
% FUNCTIONS

% SPREADING FUNCTION
for i = Bf
      for j = Bf
```

```
      S(i,j) = 10 .^((15.81+7.5 * ((i-j)+0.474)-17.5 *
            (1+((i-j)+0.474) .^2) .^0.5)/10);
      end
end


% SPREAD CRITICAL BAND SPECTRUM IS CALCULATED
% ROW VECTOR CONTAINING THE COLUMNAR SUM OF ELEMENTS
C = S*Bi';

% END OF SPREAD2.M



%
% FILE NAME: DBTOPHON.M
%
function P_XX = dbtophon(Ci)
% CONVERT SPREAD BARK SPECTRUM INTO PHON SCALE

load a:\MBSD\equal.mat  % EQUAL-LOUDNESS CONTOURS

T = 10*log10(Ci(4:18)); % COMPUTE BARK 4 TO 18 ONLY IN dB

for i = 1:1:15
      j = 1;
      while T(i) >= eqlcon(j,i)
            j = j + 1;
            if j == 16
                  fprintf(1,'ERROR\n')
            end
      end
      if j == 1
            P_XX(i) = phons(1);
      else
            t1 = (T(i) - eqlcon(j-1,i))/(eqlcon(j,i) - eqlcon(j-1,i));
            P_XX(i) = phons(j-1) + t1*(phons(j) - phons(j-1));
      end
end

% END OF DBTOPHON.M



%
% FILE NAME: SFM1.M
%
function alpha = sfm1 (XX)
% INPUT : POWER SPECTRUM
% COMPUTES SPECTRAL FLATNESS MEASURE AS FOLLOWS:
% FOR alpha = 1,  SFM <= -60 dB ENTIRELY TONE-LIKE SIGNAL
%
% FOR alpha = 0,  SFM >=   0 dB ENTIRELY NOISE-LIKE SIGNAL
```

```
Am = mean(XX);
G = sum(log10(XX))/length(XX);
Gm = 10^G;
SFM_dB = (10 * log10 (Gm/Am));
SFM_dB_max = -60;
alpha = min((SFM_dB/SFM_dB_max), 1);

% END OF SFM1.M



%
% FILE NAME: THRESH2.M
%
function Norm_Spread = thresh2 (Bf, alpha, Ci, norm)
% RECEIVES Ci IN dB AND CALCULATES NOISE MASKING THRESHOLD ESTIMATE

i = Bf;
Oi= alpha * (14.5 + i) + (1 - alpha) * 5.5;

Norm_Spread = Ci - Oi';

% END OF THRESH2.M



%
% FILE NAME: LAST_TH.M
%
function Noise_Th = last_th (Bf, Offset_XX, Abs_thresh)
% COMPUTES THE NOISE MASKING THRESHOLD CONSIDERING THE
% ABSOLUTE THRESHOLD

for i = Bf
      if Offset_XX(i) < Abs_thresh(i)
            Noise_Th(i) = Abs_thresh(i);
      else
            Noise_Th(i) = Offset_XX(i);
      end
end

% END OF LAST_TH.M



%
% FILE NAME: PHTOSN.M
%
function S_XX = phtosn(P_XX)
% CONVERT LOUDNESS LEVEL (PHON SCALE) INTO LOUDNESS (SONE SCALE)

for i = 1:1:15
      if P_XX(i) >= 40
            S_XX(i) = 2^((P_XX(i) - 40)/10);
```

```
      else
            S_XX(i) = (P_XX(i)/40)^2.642;
      end
end

% END OF PHTOSN.M



%
% FILE NAME: MARK.M
%
function Mask = mark(S_YY, S_NT)
% GENERATES THE INDICATOR OF PERCEPTIBLE DISTORTION
Mask = zeros(18,1);

for i = 4:1:18
      if S_YY(i-3) > S_NT(i-3)
            Mask(i) = 1;            % PERCEPTIBLE DISTORTION
      else
            Mask(i) = 0;            % IMPERCEPTIBLE DISTORTION
      end
end

% END OF MARK.M



%
% FILE NAME: EDIFF2.M
%
function BSD1 = ediff2(S_XX, S_YY, Mask, flag)
% CALCULATES THE MBSD VALUE FOR A FRAME

if flag == 0
      T = sum(S_XX);
else
      T = 1;
end;

for i = 1:1:15
      s(i) = Mask(i+3)*(abs(S_XX(i)-S_YY(i))/T);
end

BSD1 = mean(s);

% EMD OF EDIFF2.M
```

APPENDIX B

C PROGRAM OF EMBSD

```
/*********************************************************************

        FILE NAME: EMBSD.C
        DEVELOPER: YANG, WONHO

        USAGE: embsd original distorted flag
            where
                  embsd : command for running the program
                  original : filename of original speech
                  distorted : filename of distorted speech
                  flag : flag for speech data format
                        (0 for MSB-LSB; 1 for LSB-MSB)

        EXAMPLE: mbsd f1.d f1_coder.d 0
*********************************************************************/

#include <stdio.h>
#include <stdlib.h>
#include <math.h>
#include "embsd.h"
#include "embsd_s.c"

main( argc, argv )
int argc;
char *argv[];
{
      FILE  *fp1, *fp2, *fp3; /* FILE POINTERS */
      char  *FLAG;            /* FLAG FOR DATA FORMAT */
      int   i;
      int   j;
      int   p;
      int   q;
      int   flag;
      int   tframe;     /* TOTAL NUMBER OF FRAMES TO BE PROCESSED */
      double      distortion;
      double      MBSD;             /* MBSD VALUE */
      double      alpha;
      double      pre_MBSD;
      double      temp1;
      double      pcount;

      if ( argc >= 3 ) {    /* THERE MUST BE AT LEAST TWO PARAMETERS */

         if (( fp1 = fopen( *++argv, "rb" )) == NULL ) {
                        /* OPEN THE ORIGINAL SPEECH FILE */
            printf("ERROR : can't open %s!!\n", *argv );
            return 1;
         }
```

```
if (( fp2 = fopen( *++argv, "rb" )) == NULL ) {
              /* OPEN THE DISTORTED SPEECH FILE */
   printf("ERROR : can't open %s!!\n", *argv );
   return 1;
}
else {
   fp3 = fopen("result.res","a");

   if ( argc == 4 )
         FLAG = *++argv;   /* FLAG FOR DATA FORMAT */
   else
         FLAG = "0";       /* DEFAULT */

   prepare_for_normalization( fp1, fp2, FLAG );

   tframe = 1 + floor( (Nz - FRAME)/(FRAME/2) );
         /* TOTAL NUMBER OF FRAMES */

   initialization( fp1, fp2, tframe, FLAG );

   read_original_speech( fp1, FLAG, 2 );
         /* READ ONE FRAME OF ORIGINAL SPEECH */

   read_distorted_speech( fp2, FLAG, 2 );
         /* READ ONE FRAME OF DISTORTED SPEECH */

   pcount = 0.0;
   distortion = 0.0;
   pre_MBSD = 0.0;
   p = 0;
   q = 0;
   temp1 = 0.0;

   for ( i = 0; i < tframe; i++ ) {

         normalize();

         flag = check_frame();
         /* CHECK IF THE FRAME IS TO BE PROCESSED */

         if ( flag == 1 ) {      /* FOR NON-SILENCE FRAME */

               /* POWER SPECTRUM */
               fft_n01( 0 );
               fft_n01( 1 );

               /* BARK SPECTRUM */
               bk_frq( 0 );      /* FOR ORIGINAL */
               bk_frq( 1 );      /* FOR DISTORTED */


               for ( j = 0; j < 18; j++ ) {
                     CX[j] = BX[j];
                     CY[j] = BY[j];
```

```
        }

        /* BARK SPECTRUM IN PHON SCALE */
        dbtophon( 0 );    /* FOR ORIGINAL */
        dbtophon( 1 );    /* FOR DISTORTED */

        alpha = sfm();
              /* SPECTRAL FLANESS MEASURE*/

        thresh2( alpha );
              /* NOISE MASKING THRESHOLD IN dB */

        dbtophon( 2 );    /* NOISE MASKING THRESHOLD */

        /* CONVERSION OF PHON LEVEL INTO SONE LEVEL */
        phontoson( 0 );   /* FOR ORIGINAL */
        phontoson( 1 );   /* FOR DISTORTED */
        phontoson( 2 );
              /* FOR NOISE MASKING THRESHOLD */

        MBSD = measure(); /* MBSD FOR A FRAME */

        /* COGNITION MODEL */
        p++;
        if ( temp1 < MBSD )
              temp1 = MBSD;

        if ( p == 10 || q > 0 ) {
              pre_MBSD *= T_FACTOR;
              if ( pre_MBSD < temp1 )
                    pre_MBSD = temp1;
              distortion += pre_MBSD;
              p = 0;
              q = 0;
              temp1 = 0.0;
              pcount++;
        }
}

else {      /* FOR SILENCE FRAME */
        q++;
        if ( p > 0 || q == 10 ) {
              pre_MBSD *= T_FACTOR;
              distortion += pre_MBSD;
              p = 0;
              q = 0;
              temp1 = 0.0;
              pcount++;
        }

}

read_original_speech( fp1, FLAG, 1 );
        /* READ A HALF FRAME OF ORIGINAL SPEECH */
```

```
                    read_distorted_speech( fp2, FLAG, 1 );
                          /* READ A HALF FRAME OF DISTORTED SPEECH */

               } /* END OF FOR */

               fclose( fp1 );
               fclose( fp2 );

               fprintf(fp3, "%5.1f\n", distortion/pcount);

               fclose( fp3 );
               return 0;

         }     /* END OF ELSE */

      }  /* END OF IF */
      return 1;

}     /* END OF PROGRAM */
```

```
/*********************************************************************

        FILE NAME: EMBSD.H
        DEVELOPER: YANG, WONHO

*********************************************************************/

#include <stdio.h>
#include <stdlib.h>
#include <math.h>

#define     FRAME       320   /* FRAME SIZE IN SAMPLES */
#define     PI          3.14159265358979323846
#define     NORM        1000.0  /* NORM AMPLITUDE */
#define     BSIZE       18      /* NUMBER OF BARK FREQUENCIES */
#define     FSIZE       512     /* HALF OF FFT SIZE */
#define     N           1024    /* FFT SIZE */
#define     TWOPI       (2*3.14159265358979323846)
#define     SQRTHALF    0.70710678118654752440
#define     OFFSET      0           /* HEADER LENGTH IN BYTES */
#define     T_FACTOR    0.8

double      XMEAN;      /* DC OFFSET OF ORIGINAL SPEECH */
double      YMEAN;      /* DC OFFSET OF DISTORTED SPEECH */
double      XRMS;       /* RMS VALUE OF ORIGINAL SPEECH */
double      YRMS;       /* RMS VALUE OF DISTORTED SPEECH */
double      XTHRESHOLD; /* SILENCE THRESHOLD FOR PROCESSING */
double      YTHRESHOLD; /* SILENCE THRESHOLD FOR PROCESSING */
double      W[FRAME];   /* HANNING WINDOW */
double      FREQ[FSIZE];      /* FREQUENCY SCALE */
double      Abs_thresh[BSIZE]; /* ABSOLUTE HEARING THRESHOLD IN BARK */
int         X[FRAME];   /* ORIGINAL SPEECH */
int         Y[FRAME];   /* DISTORTED SPEECH */
double      XX[FRAME];  /* NORMALIZED ORIGINAL SPEECH */
double      YY[FRAME];  /* NORMALIZED DISTORTED SPEECH */
double      PSX[FSIZE]; /* POWER SPECTRUM OF ORIGINAL */
double      PSY[FSIZE]; /* POWER SPECTRUM OF DISTORTED */
double      BX[BSIZE];  /* BARK SPECTRUM OF ORIGINAL */
double      BY[BSIZE];  /* BARK SPECTRUM OF DISTORTED */
double      CX[BSIZE];  /* SPREAD BARK SPECTRUM OF ORIGINAL */
double      CX1[BSIZE]; /* SPREAD BARK SPECTRUM FOR NMT */
double      CY[BSIZE];  /* SPREAD BARK SPECTRUM OF DISTORTED */
double      PX[BSIZE-3];
            /* SPREAD BARK SPECTRUM OF ORIGINAL IN PHON SCALE */
double      PY[BSIZE-3];
            /* SPREAD BARK SPECTRUM OF DISTORTED IN PHON SCALE */
double      PN[BSIZE-3];
            /* SPREAD BARK SPECTRUM OF NOISE IN PHON SCALE */
double      SX[BSIZE-3];      /* SPECIFIC LOUDNESS OF ORIGINAL */
double      SY[BSIZE-3];      /* SPECIFIC LOUDNESS OF DISTORTED */
double      SN[BSIZE-3];      /* SPECIFIC LOUDNESS OF NOISE */
double      CNMT[BSIZE];
            /* NOISE MASKING THRESHOLD IN SPREAD BARK SPECTRUM */
double      ABS_TH[BSIZE];    /* ABSOLUTE HEARING THRESHOLD */
```

```
double      Nx;   /* NUMBER OF SAMPLES IN ORIGINAL SPEECH */
double      Ny;   /* NUMBER OF SAMPLES IN DISTORTED SPEECH */
double      Nz;   /* NUMBER OF SAMPLES TO BE COMPARED */
int         cur_run = 0;
double      *sncos = NULL;

double WEIGHT[15] = {1,1,1,1,1,1,1,1,1,1,1,1,1,1,1};

int         BARK[BSIZE+1] = {0, 100, 200, 300, 400, 510, 630, 770, 920,
                             1080, 1270,1480, 1720, 2000, 2320, 2700,
                             3150, 3700, 4400 };
            /* BARK FREQUENCY */

double      eqlcon[13][15] =  /* EQUAL-LOUDNESS CONTOURS */
{ {12,7,4,1,0,0,0,-0.5,-2,-3,-7,-8,-8.5,-8.5,-8.5},
  {20,17,14,12,10,9.5,9,8.5,7.5,6.5,4,3,2.5,2,2.5},
  {29,26,23,21,20,19.5,19.5,19,18,17,15,14,13.5,13,13.5},
  {36,34,32,30,29,28.5,28.5,28.5,28,27.5,26,25,24.5,24,24.5},
  {45,43,41,40,40,40,40,40,40,39.5,38,37,36.5,36,36.5},
  {53,51,50,49,48.5,48.5,49,49,49,49,48,47,46.5,45.5,46},
  {62,60,59,58,58,58.5,59,59,59,59,58,57.5,57,56,56},
  {70,69,68,67.5,67.5,68,68,68,68,68,67,66,65.5,64.5,64.5},
  {79,79,79,79,79,79,79,79,78,77.5,76,75,74.5,73,73},
  {89,89,89,89.5,90,90,90,89.5,89,88.5,87,86,85.5,84,83.5},
  {100,100,100,100,100,99.5,99,99,98.5,98,96,95,94.5,93.5,93},
  {112,112,112,112,111,110.5,109.5,109,108.5,108,106,105,104.5,103,
   102.5},
  {122,122,121,121,120.5,120,119,118,117,116.5,114.5,113.5,113,111,
   110.5}};

double  phons[13]=            /* LOUDNESS LEVELS (PHON SCALES) */
{0.0,10.0,20.0,30.0,40.0,50.0,60.0,70.0,80.0,90.0,100.0,110.0,120.0};

/* FUNCTIONS */
void hanning_window( void );
void check_original_speech1( FILE * );
void check_distorted_speech1( FILE * );
int  read_speech_sample( FILE *, char * );
void check_original_speech2( FILE *, char * );
void check_distorted_speech2( FILE *, char * );
void find_original_rms( FILE *, char * );
void find_distorted_rms( FILE *, char * );
void read_header( FILE *, FILE * );
void read_original_speech( FILE *, char *, int );
void read_distorted_speech( FILE *, char *, int );
void normalize( void );
void silence_threshold( FILE *, FILE *, int, char * );
double sfm( void );
void thresh2( double );
void init_sincos( void );
double s_sin( int );
double s_cos( int );
void scramble_real( double * );
void fft_real_to_hermitian( double * );
```

```
void fft_n01( int );
void bk_frq( int );
void thrshld( void );
void dbtophon( int );
void phontoson( int );
double measure( void );
void prepare_for_normalization( FILE *, FILE *, char * );
void initialization( FILE *, FILE *, int, char * );
int check_frame( void );
```

```
/*************************************************************************

        FILE NAME: EMBSD_S.C
        DEVELOPER: YANG, WONHO

*************************************************************************/

void hanning_window()
/* THIS FUNCTION CALCULATES HANNING WINDOW */
{
    extern double W[FRAME];
    int     i;

    for ( i = 0; i < FRAME; i++ )
            W[i] = 0.5*(1.0-cos(2.0*PI*(i+1.0)/(FRAME+1.0)));
}


void check_original_speech1( fp )
FILE    *fp;
/* THIS FUNCTION READS AN ORIGINAL BINARY SPEECH FILE
   AND FIND OUT THE NUMBER OF SAMPLES IN THAT FILE */
{
    extern double Nx;   /* NUMBER OF SAMPLES IN ORIGINAL SPEECH */
    int           t;
    double        k;

    k = 0.0;
    while( !feof( fp ) ) {
            t = getc( fp );  /* GET 2 BYTES */
            t = getc( fp );
            k++;
    }
    Nx = k - (double)OFFSET;
    rewind( fp );
}


void check_distorted_speech1( fp )
FILE    *fp;
/* THIS FUNCTION READS AN ORIGINAL BINARY SPEECH FILE
   AND FIND OUT THE NUMBER OF SAMPLES IN THAT FILE */
{
    extern double Ny;
    int           t;
    double        k;

    k = 0.0;
    while( !feof( fp ) ) {
            t = getc( fp );  /* GET 2 BYTES */
            t = getc( fp );
            k++;
    }
    Ny = k - (double)OFFSET;
```

```
    rewind( fp );
}


int read_speech_sample( fp, FLAG )
FILE *fp;
char *FLAG;
/* THIS FUNCTION READS A SPEECH SAMPLE FROM A FILE */
{
    int     MSB, LSB, sign, n, n1, t;
    int     check = 0x00ff;

    if ( *FLAG == '0' ) {     /* MSB-LSB FORMAT */
            MSB = getc( fp );  /* GET ONE BYTE */
            LSB = getc( fp );  /* GET ONE BYTE */

            sign = MSB;
            sign = sign >> 7;
            if ( sign == 0 )  /* POSITIVE */
                  n = MSB;
            else {            /* NEGATIVE */
                  t = ~MSB;
                  n = t & check;
                  n = -1 * n;
            }

            if ( sign == 1 ) {      /* NEGATIVE */
                  t = ~LSB;
                  n1 = t & check;
                  n1 = -1 * n1 - 1;
                  n = n * 256 + n1;
            }
            else                    /* POSITIVE */
                  n = n * 256 + LSB;

    } /* END OF IF */

    else {    /* LSB-MSB FORMAT */
            LSB = getc( fp );  /* GET ONE BYTE */
            MSB = getc( fp );  /* GET ONE BYTE */

            sign = MSB;
            sign = sign >> 7;
            if ( sign == 0 )  /* POSITIVE */
                  n = MSB;
            else {                        /* NEGATIVE */
                  t = ~MSB;
                  n = t & check;
                  n = -1 * n;
            }

            if ( sign == 1 ) {      /* NEGATIVE */
                  t = ~LSB;
                  n1 = t & check;
```

```
                n1 = -1 * n1 - 1;
                n = n * 256 + n1;
            }
            else                    /* POSITIVE */
                n = n * 256 + LSB;

      }     /* END OF ELSE */

      return n;

}


void check_original_speech2( fp, FLAG )
FILE    *fp;
char    *FLAG;
/* THIS FUNCTION READS A BINARY SPEECH FILE AND FIND OUT
   DC OFFSET OF THE SPEECH SIGNAL */
{
    extern double  XMEAN;
    extern double  Nz;
    int     n;
    double  k;
    double  temp1 = 0.0;

    k = 0.0;

    while( k < Nz + (double)OFFSET ) {
            n = read_speech_sample( fp, FLAG );

            if ( k >= OFFSET )
                temp1 += (double)n;           /* SUM */
            k++;

    } /* END OF WHILE */

    XMEAN = temp1 / ( k - (double)OFFSET );     /* MEAN */
    rewind( fp );
}


void check_distorted_speech2( fp, FLAG )
FILE    *fp;
char    *FLAG;
/* THIS FUNCTION READS A BINARY SPEECH FILE AND FIND OUT
   DC OFFSET OF THE SPEECH SIGNAL */
{
    extern double  YMEAN;
    extern double  Nz;
    int     n;
    double  k;
    double  temp1 = 0.0;

    k = 0.0;
```

```
    while( k < Nz + (double)OFFSET ) {
            n = read_speech_sample( fp, FLAG );

            if ( k >= OFFSET )
                  temp1 += (double)n;   /* SUM */
            k++;
    } /* END OF WHILE */
    YMEAN = temp1 / ( k - (double)OFFSET );     /* MEAN */
    rewind( fp );
}


void find_original_rms( fp, FLAG )
FILE    *fp;
char    *FLAG;
/* THIS FUNCTION READS A BINARY SPEECH FILE AND FIND OUT
   RMS VALUE OF THE SPEECH SIGNAL */
{
    extern double  XMEAN;     /* DC OFFSET OF ORIGINAL SPEECH */
    extern double  XRMS;      /* RMS VALUE OF ORIGINAL SPEECH */
    extern double  Nz;
    int     n;
    double  k;
    double  temp1;
    double  temp2 = 0.0;

    k = 0.0;
    while( k < Nz + (double)OFFSET ) {
            n = read_speech_sample( fp, FLAG );

            if ( k >= OFFSET ) {
                  temp1 = (double)n - XMEAN;
                  temp2 += temp1 * temp1;
            }
            k++;

    } /* END OF WHILE */
    XRMS = sqrt(temp2 /( k - (double)OFFSET));
    rewind( fp );
}


void find_distorted_rms( fp, FLAG )
FILE    *fp;
char    *FLAG;
/* THIS FUNCTION READS A BINARY SPEECH FILE AND FIND OUT
   RMS VALUE OF THE SPEECH SIGNAL */
{
    extern double  YMEAN;     /* DC OFFSET OF DISTORTED SPEECH */
    extern double  YRMS;      /* RMS VALUE OF DISTORTED SPEECH */
    extern double  Nz;
    int     n;
    double  k;
    double  temp1;
```

```
    double  temp2 = 0.0;

    k = 0;

    while( k < Nz + (double)OFFSET ) {
            n = read_speech_sample( fp, FLAG );

            if ( k >= OFFSET ) {
                  temp1 = (double)n - YMEAN;
                  temp2 += temp1 * temp1;
            }
            k++;
    } /* END OF WHILE */
    YRMS = sqrt(temp2 / ( k - (double)OFFSET ));
    rewind( fp );
}


void read_header( fp1, fp2 )
FILE  *fp1;
FILE  *fp2;
/* THIS FUNCTION READS HEADER OF BINARY SPEECH FILES */
{
    int     t;
    int     k;

    k = 0;
    while( k < OFFSET ) {
            t = getc( fp1 );  /* GET ONE BYTE */
            t = getc( fp1 );  /* GET ONE BYTE */
            t = getc( fp2 );  /* GET ONE BYTE */
            t = getc( fp2 );  /* GET ONE BYTE */
            k++;
    } /* END OF WHILE */
}


void read_original_speech( fp, FLAG, p )
FILE    *fp;
char    *FLAG;
int     p;  /* p = 1 FOR READING REAR HALF FRAME
               p = 2 FOR READING A FRAME */
/* THIS PROGRAM READS A BINARY SPEECH FILE IN WHICH
A SAMPLE IS A 2 BYTE INTEGER AS AN INPUT AND WRITES
THOSE INTEGERS. THESE 2 BYTES ARE STORED IN MSB-LSB
OR LSB-MSB. IF SAMPLES ARE STORED IN MSB-LSB, FLAG
SHOULD BE "0". OTHERWISE, FLAG SHOULD BE "1".
IF flag IS 0, THIS PROGRAM READS THE ORIGINAL SPEECH.
IF flag IS 1, THIS PROGRAM READS THE DISTORTED SPEECH. */

{
    extern int  X[FRAME];
    int     n;
    int     k;
```

```
    int     i;

    k = 0;
    if ( p == 1 ) /* READING HALF FRAME */
            for ( i = 0; i < FRAME/2; i++ ) /* OVERLAPPED HALF FRAME */
                  X[i] = X[i+FRAME/2];

    while( k < p * (FRAME/2) ) {
            n = read_speech_sample( fp, FLAG );

            if ( p == 1 )
                  X[(FRAME/2)+k] = n;
                        /* STORE A SPEECH SAMPLES IN AN ARRAY */
            else
                  X[k] = n;

            k++;
    } /* END OF WHILE */
}


void read_distorted_speech( fp, FLAG, p )
FILE    *fp;
char    *FLAG;
int         p;    /* p = 1 FOR READING REAR HALF FRAME
                     p = 2 FOR READING A FRAME */

/* THIS PROGRAM READS A BINARY SPEECH FILE IN WHICH
A SAMPLE IS A 2 BYTE INTEGER AS AN INPUT AND WRITES
THOSE INTEGERS. THESE 2 BYTES ARE STORED IN MSB-LSB
OR LSB-MSB. IF SAMPLES ARE STORED IN MSB-LSB, FLAG
SHOULD BE "0". OTHERWISE, FLAG SHOULD BE "1".
IF flag IS 0, THIS PROGRAM READS THE ORIGINAL SPEECH.
IF flag IS 1, THIS PROGRAM READS THE DISTORTED SPEECH. */

{
    extern int  Y[FRAME];
    int     n;
    int     k;
    int     i;

    k = 0;
    if ( p == 1 )
            for ( i = 0; i < FRAME/2; i++ )
                  Y[i] = Y[i+FRAME/2];

    while( k < p * (FRAME/2) ) {
            n = read_speech_sample( fp, FLAG );

            if ( p == 1 )
                  Y[(FRAME/2)+k] = n;
                        /* STORE A SPEECH SAMPLES IN AN ARRAY */
            else
                  Y[k] = n;
```

```
            k++;

    } /* END OF WHILE */
}


void normalize()
/* THIS FUNCTION NORMALIZE TWO INPUT SIGNALS */
{
      extern int X[FRAME];       /* ORIGINAL SPEECH */
      extern int Y[FRAME];   /* DISTORTED SPEECH */
      extern double XX[FRAME];   /* NORMALIZED ORIGINAL SPEECH */
      extern double YY[FRAME];   /* NORMALIZED DISTORTED SPEECH */
      extern double     XMEAN;
      extern double     YMEAN;
      extern double     XRMS;
      extern double     YRMS;
      int     i;

      for ( i = 0; i < FRAME; i++ ) {
            XX[i] = (double)X[i] - XMEAN;
            YY[i] = (double)Y[i] - YMEAN;
      }
      for ( i = 0; i < FRAME; i++ ) {
            XX[i] = NORM * XX[i] / XRMS;
            YY[i] = NORM * YY[i] / YRMS;
      }
}


void silence_threshold( fp1, fp2, tframe, FLAG )
FILE  *fp1;
FILE  *fp2;
int   tframe;
char  *FLAG;

/* THIS FUNCTION DETERMINES THE THRESHOLD FOR A SILENCE FRAME */
{
      extern double W[FRAME];
      extern double XX[FRAME];
      extern double YY[FRAME];
      extern double XTHRESHOLD; /* SILENCE THRESHOLD FOR PROCESSING */
      extern double YTHRESHOLD; /* SILENCE THRESHOLD FOR PROCESSING */
      int     i, j;
      double  xenergy, max_xenergy;
      double  yenergy, max_yenergy;

      read_header( fp1, fp2 );

      max_xenergy = 0.0;
      max_yenergy = 0.0;

      read_original_speech( fp1, FLAG, 2 );
      read_distorted_speech( fp2, FLAG, 2 );
```

```
      for ( j = 0; j < tframe; j++ ) {
            normalize();
            xenergy = 0.0;
            yenergy = 0.0;

            for ( i = 0; i < FRAME; i++ ) {
                  xenergy += (XX[i] * W[i])*(XX[i] * W[i]);
                  yenergy += (YY[i] * W[i])*(YY[i] * W[i]);
            }
            if ( xenergy > max_xenergy )
                  max_xenergy = xenergy;
            if ( yenergy > max_yenergy )
                  max_yenergy = yenergy;

            read_original_speech( fp1, FLAG, 1 );
            read_distorted_speech( fp2, FLAG, 1 );

      }

      XTHRESHOLD = pow(10.0, -1.5) * max_xenergy;    /* 15dB BELOW */
      YTHRESHOLD = pow(10.0, -3.5) * max_yenergy;    /* 35dB BELOW */

      rewind( fp1 );
      rewind( fp2 );
}


double sfm()
/* USING POWER SPECTRUM OF ORIGINAL SPEECH,
   THIS FUNCTION COMPUTES THE SPECTRAL FLATNESS MEASURE.
      for alpha = 1, SFM <= -60 dB : entirely tone-like signal
      for alpha = 0, SFM >= 0 dB : entirely noise-like signal
*/

{
      extern double PSX[FSIZE]; /* POWER SPECTRUM OF ORIGINAL */
      double  alpha;
      double  a_mean;         /* ALGEBRAIC MEAN */
      double  g_mean;         /* GEOMETRIC MEAN */
      int     i;
      double  sum1, sum2;
      double  sfm_db, sfm_db_ratio;
      double  t;

      sum1 = 0.0;
      sum2 = 0.0;
      for ( i = 0; i < FSIZE; i++ ) {
            sum1 += PSX[i];
            sum2 += log10( PSX[i] );
      }
      a_mean = sum1 / (double)FSIZE;
      t = sum2 / (double)FSIZE;
      g_mean = pow( 10.0, t );
```

```
      sfm_db = 10.0 * log10( g_mean / a_mean );
      sfm_db_ratio = sfm_db / -60.0;

      if ( sfm_db_ratio < 1 )
            alpha = sfm_db_ratio;
      else
            alpha = 1;

      return alpha;

}


void thresh2( alpha )
double alpha;
/* USING SPREAD BARK SPECTRUM IN DB, THIS FUNCTION
CALCULATES NOISE MASKING THRESHOLD */

{
    extern double   CX[BSIZE];   /* SPREAD BARK SPECTRUM OF ORIGINAL */
    extern double   CNMT[BSIZE];
                  /* NOISE MASKING THRESHOLD IN SPREAD SPECTRUM */
    extern double   ABS_TH[BSIZE];
    int     i;
    double  t, tt;

    for ( i = 0; i < BSIZE; i++ ) {
      t = alpha * ( 14.5 + (double)i + 1.0 ) + ( 1.0 - alpha ) * 5.5;
      tt = 10.0 * log10(CX[i]) - t;

      if ( tt < ABS_TH[i] )
            CNMT[i] = pow(10.0, ABS_TH[i]/10.0);
      else
            CNMT[i] = pow(10.0, tt/10.0);

    }
}

/* fft_real.c** Routines for split-radix, real-only transforms.
These routines are adapted from [Sorenson 1987] * * When all x[j] are
real the standard DFT of (x[0],x[1],...,x[N-1]),* call it x^, has the
property of Hermitian symmetry: x^[j] =x^[N-j].
Thus we only need to find the set (x^[0].re, x^[1].re,..., x^[N/2].re,
x^[N/2-1].im, ..., x^[1].im) * which, like the original signal x, has N
elements.* The two key routines perform forward (real-to-Hermitian)
FFT, and * backward (Hermitian-to-real) FFT, respectively. For example,
the* sequence: fft_real_to_hermitian(x, N);
      fftinv_hermitian_to_real(x, N); is an identity operation on the
signal x. To convolve twopure-real signals x and y, one does:
fft_real_to_hermitian(x, N);fft_real_to_hermitian(y, N);
mul_hermitian(y, x, N);fftinv_hermitian_to_real(x, N); and x is the
pure-real cyclic convolution of x and y. */
```

```
void init_sincos()
{
      extern int        cur_run;
      extern double     *sncos;
      int               j;
      double            e = TWOPI / N;

      if ( N <= cur_run )
            return;

      cur_run = N;

      if ( sncos )
            free( sncos );

      sncos = (double *)malloc(sizeof(double) * ( 1 + ( N >> 2 )));

      for ( j = 0; j <= ( N >> 2 ); j++ )
            sncos[j] = sin( e * j );

}


double s_sin( n )
int   n;
{
      extern int        cur_run;
      extern double     *sncos;
      int               seg = n / (cur_run >> 2);

      switch (seg) {
            case 0:
                  return (sncos[n]);
            case 1:
                  return (sncos[(cur_run >> 1) - n]);
            case 2:
                  return (-sncos[n - (cur_run >> 1)]);
            case 3:
                  return (-sncos[cur_run - n]);
      }
}


double s_cos( n )
int   n;
{
      extern int        cur_run;
      int               quart = (cur_run >> 2);

      if (n < quart)
            return (s_sin(n + quart));

      return (-s_sin(n - quart));
}
```

```
void scramble_real( x )
double      *x;
{
      register int i, j, k;
      double tmp;

      for ( i = 0, j = 0; i < N - 1; i++ ) {
            if ( i < j ) {
                  tmp = x[j];
                  x[j] = x[i];
                  x[i] = tmp;
            }
            k = N / 2;
            while ( k <= j ) {
                  j -= k;
                  k >>= 1;
            }
            j += k;
      }
}


void fft_real_to_hermitian( z )
double      *z;

/*
 * Output is {Re(z^[0]),...,Re(z^[n/2),Im(z^[n/2-1]),...,Im(z^[1]).
 * This is a decimation-in-time, split-radix algorithm.
 */
{
      extern int  cur_run;
      register double cc1, ss1, cc3, ss3;
      register int is, id, i0, i1, i2, i3, i4, i5, i6, i7, i8, a, a3,
b, b3, nminus = N - 1, dil, expand;
      register double *x, e;
      int nn = N >> 1;
      double t1, t2, t3, t4, t5, t6;
      register int n2, n4, n8, i, j;

      init_sincos();
      expand = cur_run / N;
      scramble_real( z );
      x = z - 1;              /* FORTRAN compatibility. */
      is = 1;
      id = 4;
      do {
            for ( i0 = is; i0 <= N; i0 += id) {
                  i1 = i0 + 1;
                  e = x[i0];
                  x[i0] = e + x[i1];
                  x[i1] = e - x[i1];
            }
            is = ( id << 1 ) - 1;
            id <<= 2;
```

```
} while ( is < N );

n2 = 2;
   while ( nn >>= 1 ) {
         n2 <<= 1;
         n4 = n2 >> 2;
         n8 = n2 >> 3;
         is = 0;
         id = n2 << 1;
         do {
               for ( i = is; i < N; i += id ) {
                     i1 = i + 1;
                     i2 = i1 + n4;
                     i3 = i2 + n4;
                     i4 = i3 + n4;
                     t1 = x[i4] + x[i3];
                     x[i4] -= x[i3];
                     x[i3] = x[i1] - t1;
                     x[i1] += t1;
                     if ( n4 == 1 )
                           continue;
                     i1 += n8;
                     i2 += n8;
                     i3 += n8;
                     i4 += n8;
                     t1 = ( x[i3] + x[i4] ) * SQRTHALF;
                     t2 = ( x[i3] - x[i4] ) * SQRTHALF;
                     x[i4] = x[i2] - t1;
                     x[i3] = -x[i2] - t1;
                     x[i2] = x[i1] - t2;
                     x[i1] += t2;
               }
               is = (id << 1) - n2;
               id <<= 2;
         } while ( is < N);

         dil = N / n2;
         a = dil;
         for ( j = 2; j <= n8; j++ ) {
               a3 = ( a + ( a << 1 )) & nminus;
               b = a * expand;
               b3 = a3 * expand;
               cc1 = s_cos(b);
               ss1 = s_sin(b);
               cc3 = s_cos(b3);
               ss3 = s_sin(b3);
               a = (a + dil) & nminus;
               is = 0;
               id = n2 << 1;
               do {
                     for ( i = is; i < N; i += id ) {
                           i1 = i + j;
                           i2 = i1 + n4;
                           i3 = i2 + n4;
```

```
                              i4 = i3 + n4;
                              i5 = i + n4 - j + 2;
                              i6 = i5 + n4;
                              i7 = i6 + n4;
                              i8 = i7 + n4;
                              t1 = x[i3] * cc1 + x[i7] * ss1;
                              t2 = x[i7] * cc1 - x[i3] * ss1;
                              t3 = x[i4] * cc3 + x[i8] * ss3;
                              t4 = x[i8] * cc3 - x[i4] * ss3;
                              t5 = t1 + t3;
                              t6 = t2 + t4;
                              t3 = t1 - t3;
                              t4 = t2 - t4;
                              t2 = x[i6] + t6;
                              x[i3] = t6 - x[i6];
                              x[i8] = t2;
                              t2 = x[i2] - t3;
                              x[i7] = -x[i2] - t3;
                              x[i4] = t2;
                              t1 = x[i1] + t5;
                              x[i6] = x[i1] - t5;
                              x[i1] = t1;
                              t1 = x[i5] + t4;
                              x[i5] -= t4;
                              x[i2] = t1;
                        }
                        is = (id << 1) - n2;
                        id <<= 2;
                  } while ( is < N );
            } /* END OF for */

      } /* END OF while */
} /* END OF function */


void fft_n01( flag )
/* CALCULATE POWER SPECTRUM
   IF flag IS 0, CALCULATE POWER SPECTRUM OF ORIGINAL SPEECH
   IF flag IS 1, CALCULATE POWER SPECTRUM OF DISTORTED SPEECH */
int   flag;
{
      extern double     W[FRAME];       /* HANNING WINDOW */
      extern double     FREQ[FSIZE];       /* FREQUENCY SCALE */
      extern double     XX[FRAME]; /* NORMALIZED ORIGINAL SPEECH */
      extern double     YY[FRAME]; /* NORMALIZED DISTORTED SPEECH */
      extern double     PSX[FSIZE];   /* POWER SPECTRUM OF ORIGINAL */
      extern double     PSY[FSIZE];   /* POWER SPECTRUM OF DISTORTED */
      int i;
      double xxa[N];
      double x[N];
      double t;

      if ( flag == 0 )
            for ( i = 0; i < FRAME; i++ )
```

```
                x[i] = XX[i] * W[i];
        else
                for ( i = 0; i < FRAME; i++ )
                        x[i] = YY[i] * W[i];

        for ( i = FRAME; i < N; i++ )
                x[i] = 0.0;

        fft_real_to_hermitian( x );

        for ( i = 0; i < N; i++ ){

                if ( i == 0 ) /* || i == FSIZE/2 ) */
                        xxa[i] = x[i] * x[i] / (double)N;
                else
                        xxa[i] = ( x[i]*x[i] + x[N-i]*x[N-i] ) / (double)N;

                if ( i > 0 )
                        xxa[i] *= 2.0;

        }

        for ( i = 0; i < FSIZE; i++ ) {
                t = 8000.0/ (double)N;
                FREQ[i] =  i * t;
                if ( flag == 0 )
                        PSX[i] = xxa[i];
                else
                        PSY[i] = xxa[i];
        }
}


void bk_frq( flag )
int   flag;
/*          Computes Critcal Bands in the Bark Spectrum           */
{
        extern int        BARK[BSIZE+1];
        extern double     FREQ[FSIZE];
        extern double     PSX[FSIZE];   /* POWER SPECTRUM OF ORIGINAL */
        extern double     PSY[FSIZE];   /* POWER SPECTRUM OF DISTORTED */
        extern double     BX[BSIZE];    /* BARK SPECTRUM OF ORIGINAL */
        extern double     BY[BSIZE];    /* BARK SPECTRUM OF DISTORTED */
        int   i,j;

        if ( flag == 0 ) {
                for ( i = 0; i < BSIZE; i++ )
                BX[i] = 0.0;

                for ( i = 0; i < BSIZE; i++ )
                        for( j = 0; j < FSIZE; j++ )
                                if( BARK[i] <= FREQ[j] && FREQ[j] < BARK[i+1] )
                                        /* redo this freq j */
                                        BX[i] += PSX[j];
```

```
      }
      else {
            for ( i = 0; i < BSIZE; i++ )
                  BY[i] = 0.0;

            for ( i = 0; i < BSIZE; i++ )
                  for( j = 0; j < FSIZE; j++ )
                        if( BARK[i] <= FREQ[j] && FREQ[j] < BARK[i+1] )
                              /* redo this freq j */
                              BY[i] += PSY[j];
      }
}


void thrshld()

/* Estimate the threshold of hearing in dB by the formula of Terhardt

      thrshld(f) = { 3.64(f/1000)^(-0.8) - 6.5exp[-0.6(f/1000 - 3.3)^2]
             + 0.001(f/1000)^4 }

 This Formula produces threshold of hearing in dB
 Reference : Terhardt, E., Stoll, G. and Seewann, M, "Algorithm for
       extraction of pitch and pitch salience from complex
       tonal signals", J. Acoust. Soc. Am., vol. 71(3), Mar., 1982
*/
{
      extern double  Abs_thresh[BSIZE];
                        /* ABSOLUTE HEARING THRESHOLD IN BARK */
      extern int        BARK[BSIZE+1];     /* BARK FREQUENCY */
      extern double     FREQ[FSIZE];       /* FREQUENCY SCALE */
      int k = 0;
      int i;
      int j;
      double f;
      double L[FSIZE];
      double xox, xox1, xox2, SUM;

      SUM = 0.0;
      for( i = 0; i < FSIZE-1; i++ ) {
            f = FREQ[i+1]/1000.0;
            xox = f * f;
            xox *= xox;
            xox = 0.001 * xox;
            xox1 = pow( f, 0.8);
            xox1 = 3.64 / xox1;
            xox2 = f - 3.3;
            xox2 *= xox2;
            xox2 = .6 * xox2;
            xox2 = -1.0 * xox2;
            xox2 = 6.5 * exp( xox2 );
            L[i+1] = xox1 - xox2 + xox;
      }
```

```
	L[0] = 0.0;

	for( i = 1; i <= 18; i++ ){

		for( j = 1; j < FSIZE; j++ ){

			if ( BARK[i-1] <= FREQ[j] && FREQ[j] < BARK[i] ){
				SUM += L[j];
				k++;
			}
			else {
				SUM = 0.0;
				k = 1;
			}

		}
		Abs_thresh[i-1] = SUM / k;
	}
}


void dbtophon( flag )
/* CONVERT SPREAD BARK SPECTRUM INTO PHON SCALE */
int   flag;
{

	extern double  CX[BSIZE]; /* SPREAD BARK SPECTRUM OF ORIGINAL */
	extern double  CY[BSIZE]; /* SPREAD BARK SPECTRUM OF DISTORTED */
	extern double  CNMT[BSIZE];
			/* NOISE MASKING THRESHOLD IN SPREAD BARK SPECTRUM */
	extern double  PX[BSIZE-3];
			/* SPREAD BARK SPECTRUM OF ORIGINAL IN PHON SCALE */
	extern double  PY[BSIZE-3];
			/* SPREAD BARK SPECTRUM OF DISTORTED IN PHON SCALE */
	extern double  PN[BSIZE-3];
			/* SPREAD BARK SPECTRUM OF NOISE IN PHON SCALE */
	int i;
	int j;
	double t1;
	double T[BSIZE-3]={0};

	if ( flag == 0 ) {	/* FOR ORIGINAL SPEECH */
		for( i = 0; i < BSIZE-3; i++ )
			T[i] = 10.0 * log10( CX[i] );

		for( i = 0; i < BSIZE-3; i++ ){
			j = 0;
			while( T[i] >= eqlcon[j][i] )
				j++;
			if( j == BSIZE-3 )
				break;
			if( j == 0 )
				PX[i] = phons[0];
			else {
```

```
                        t1 = ( T[i] - eqlcon[j-1][i] ) / ( eqlcon[j][i]
- eqlcon[j-1][i] );
                        PX[i] = phons[j-1] + t1 * (phons[j] - phons[j-
1]);
                  }
            }
      }

      else if ( flag == 1 ) { /* FOR DISTORTED SPEECH */
            for( i = 0; i < BSIZE-3; i++ )
                  T[i] = 10.0 * log10( CY[i] );

            for( i = 0; i < BSIZE-3; i++ ){
                  j = 0;
                  while( T[i] >= eqlcon[j][i] )
                        j++;
                  if( j == BSIZE-3 )
                        break;
                  if( j == 0 )
                        PY[i] = phons[0];
                  else {
                        t1 = ( T[i] - eqlcon[j-1][i] ) / ( eqlcon[j][i]
- eqlcon[j-1][i] );
                        PY[i] = phons[j-1] + t1 * (phons[j] - phons[j-
1]);
                  }
            }
      }

      else {      /* FOR NOISE MASKING THRESHOLD */
            for( i = 0; i < BSIZE-3; i++ )
                  T[i] = 10.0 * log10( CNMT[i] );

            for( i = 0; i < BSIZE-3; i++ ){
                  j = 0;
                  while( T[i] >= eqlcon[j][i] )
                        j++;
                  if( j == BSIZE-3 )
                        break;
                  if( j == 0 )
                        PN[i] = phons[0];
                  else {
                        t1 = ( T[i] - eqlcon[j-1][i] ) / ( eqlcon[j][i]
- eqlcon[j-1][i] );
                        PN[i] = phons[j-1] + t1 * (phons[j] - phons[j-
1]);
                  }
            }
      }

}
```

```
void phontoson( flag )
/* CONVERT LOUDNESS LEVEL (PHON SCALE) INTO LOUDNESS (SONE SCALE) */
int   flag;
{
      extern double     PX[BSIZE-3];
            /* SPREAD BARK SPECTRUM OF ORIGINAL IN PHON SCALE */
      extern double     PY[BSIZE-3];
            /* SPREAD BARK SPECTRUM OF DISTORTED IN PHON SCALE */
      extern double     PN[BSIZE-3];
            /* SPREAD BARK SPECTRUM OF NOISE IN PHON SCALE */
      extern double     SX[BSIZE-3];
                        /* SPECIFIC LOUDNESS OF ORIGINAL */
      extern double     SY[BSIZE-3];
                        /* SPECIFIC LOUDNESS OF DISTORTED */
      extern double     SN[BSIZE-3];
                        /* SPECIFIC LOUDNESS OF NOISE */
      int         i;
      double      xox;

      if ( flag == 0 ) {      /* FOR ORIGINAL SPEECH */
            for( i = 0; i < BSIZE-3; i++ )
                  if( PX[i] >= 40.0 ){
                        xox = PX[i] - 40.0;
                        xox *= 0.1;
                        SX[i] = pow( 2.0, xox );
                  }
                  else{
                        xox = PX[i] / 40.0;
                        SX[i] = pow( xox, 2.642 );
                  }
      }

      else if ( flag == 1 ) {       /* FOR DISTORTED SPEECH */
            for( i = 0; i < BSIZE-3; i++ )
                  if( PY[i] >= 40.0 ){
                        xox = PY[i] - 40.0;
                        xox *= 0.1;
                        SY[i] = pow( 2.0, xox );
                  }
                  else{
                        xox = PY[i] / 40.0;
                        SY[i] = pow( xox, 2.642 );
                  }
      }

      else {            /* FOR NOISE MASKING THRESHOLD */
            for( i = 0; i < BSIZE-3; i++ )
                  if( PN[i] >= 40.0 ){
                        xox = PN[i] - 40.0;
                        xox *= 0.1;
                        SN[i] = pow( 2.0, xox );
                  }
                  else{
                        xox = PN[i] / 40.0;
```

```
                        SN[i] = pow( xox, 2.642 );
                }
        }

}


double measure()
/* METRIC ESTIMATING DISTORTION */
{
        extern double     SX[BSIZE-3];
                          /* SPECIFIC LOUDNESS OF ORIGINAL */
        extern double     SY[BSIZE-3];
                          /* SPECIFIC LOUDNESS OF DISTORTED */
        extern double     SN[BSIZE-3];
                  /* SPECIFIC LOUDNESS OF NOISE MASKING THRESHOLD */
        int         i;
        double      dist = 0.0;
        double      temp;
        double      x;
        double      ww;
        double      w1;
        double      temp1, temp2;
        extern double WEIGHT[15];

        temp1 = 1.0;
        temp2 = 1.0;

        for ( i = 0; i < 15; i++ ) {
              temp1 += SX[i];
              temp2 += SY[i];
        }
        w1 = temp1 / temp2;

        dist = 0.0;

        for ( i = 0; i < BSIZE-3; i++ ) {
              ww = w1;
              temp = fabs( SX[i] - ww*SY[i] );
              x = temp - SN[i];

              if ( x > 0.0 )
                    dist += WEIGHT[i]*x;
        }

        return dist;
}


void prepare_for_normalization( fp1, fp2, FLAG )
FILE  *fp1;
FILE  *fp2;
char  *FLAG;
{
```

```
      extern double     Nx;    /* NUMBER OF SAMPLES OF ORIGINAL */
      extern double     Ny;    /* NUMBER OF SAMPLES OF DISTORTED */
      extern double     Nz;    /* NUMBER OF SAMPLES TO BE COMPARED */

      check_original_speech1( fp1 );
      check_distorted_speech1( fp2 );

      if ( Nx < Ny )
            Nz = Nx;
      else
            Nz = Ny;

      check_original_speech2( fp1, FLAG );
      check_distorted_speech2( fp2, FLAG );

      find_original_rms( fp1, FLAG );
      find_distorted_rms( fp2, FLAG );
}


void initialization( fp1, fp2, tframe, FLAG )
FILE  *fp1;
FILE  *fp2;
int   tframe;
char  *FLAG;
{
      int         i;
      double      t;
      extern double     FREQ[FSIZE];

      for ( i = 0; i < FSIZE; i++ ) {
            t = 8000.0/ (double)N;
            FREQ[i] =  i * t;
      }

      hanning_window(); /* HANNING WINDOW */
      thrshld();        /* ABSOLUTE HEARING THRESHOLD */
      silence_threshold( fp1, fp2, tframe, FLAG );
}


int check_frame()
{
      extern double  W[FRAME];
      extern double  XX[FRAME]; /* NORMALIZED ORIGINAL SPEECH */
      extern double  YY[FRAME]; /* NORMALIZED DISTORTED SPEECH */
      extern double  XTHRESHOLD; /* SILENCE THRESHOLD FOR PROCESSING */
      extern double  YTHRESHOLD; /* SILENCE THRESHOLD FOR PROCESSING */
      double      xenergy;
      double      yenergy;
      int         i;
      int         flag;

      xenergy = 0.0;
```

```
        yenergy = 0.0;
        for ( i = 0; i < FRAME; i++ ) {
              xenergy += (XX[i] * W[i])*(XX[i] * W[i]);
              yenergy += (YY[i] * W[i])*(YY[i] * W[i]);
        }

        if ( xenergy > XTHRESHOLD && yenergy > YTHRESHOLD )
              flag = 1;
        else
              flag = 0;

        return flag;

}
```

APPENDIX C

GLOSSARY

ABS coders : Analysis-By-Synthesis coders

ACR: Absolute Category Rating

ADPCM: Adaptive Differential Pulse Code Modulation

AGC: Automatic Gain Control

AMPS: Advanced Mobile Phone Service

BSD: Bark Spectral Distortion

BT: British Telecom

CD: Cepstral Distance

CDMA: Code Division Multiple Access

CELP: Codebook Excitation Linear Prediction

DCR: Degradation Category Rating

DMOS: Degradation Mean Opinion Score

DT: Deutsche Telekom

EMBSD: Enhanced Modified Bark Spectral Distortion

EVRC: Enhanced Variable Rate Codec

FMNB: Frequency Measuring Normalizing Blocks

GSM: Global System for Mobile Telecommunications

IP: Internet Protocol

ITU: Internaltional Telecommunication Union

LLR: Log Likelihood Ratio

MBSD: Modified Bark Spectral Distortion

MNB: Measuring Normalizing Blocks

MNRU: Modulated Noise Reference Unit

MOS: Mean Opinion Score

OBQ measure: Output-Based Quality measure

PAMS: Perceptual Analysis Measurement System

PAQM: Perceptual Audio Quality Measure

PSQM: Perceptual Speech Quality Measure

RF: Radio Frequency

SEE: Standard Error of the Estimates

SFM: Spectral Flatness Measure

SNR: Signal-to-Noise Ratio

SNRseg: Segmental Signal-to-Noise Ratio

SPL: Sound Pressure Level

TDMA: Time Division Multiple Access

TMNB: Time Measuring Normalizing Blocks

TOSQA: Telecommunication Objective Speech Quality Assessment