REAL-TIME NON-INTRUSIVE SPEECH QUALITY ESTIMATION OF VOICE OVER INTERNET PROTOCOL USING GENETIC PROGRAMMING

By

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SUBMITTED IN FULFILLMENT OF THE
REQUIREMENTS FOR THE DEGREE OF
DOCTOR OF PHILOSOPHY
AT
UNIVERSITY OF LIMERICK
LIMERICK, IRELAND
JUNE 2008

UNIVERSITY OF LIMERICK
DEPARTMENT OF
ELECTRONIC AND COMPUTER ENGINEERING

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Dated: June 2008

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Department: **Electronic and Computer Engineering**

Degree: **Ph.D.** Convocation: **August** Year: **2008**

I hereby declare that this thesis is entirely my own work and that it has not been submitted for any other academic award.

Signature of Author

To Late Grandparents

and

Istvan Matyasovszki

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List of Acronyms

ACR Absolute Category Rating

AMR Adaptive Multi-Rate

ANN Artificial Neural Network

br bit-rate

clp conditional loss probability

dB Decibel

dBov Decibel relative to the overload point of a digital system

DCR Degradation Category Rating

DTX Discontinuous Transmission

fd frame duration

FEC Forward Error Correction

GA Genetic Algorithm

GP Genetic Programming

GMM Gaussian Mixture Model

GSM Global System for Mobile Communication

HMM Hidden Markov Model

ISDN Integrated Services Digital Network

ITU-T International Telecommunication Union–Telecommunication Standardization Sector

mbl mean burst length

mlr mean loss rate

MOS Mean Opinion Score

MOS-LQO Mean Opinion Score–Listening Quality Objective

MOS-LQS Mean Opinion Score–Listening Quality Subjective

MSE Mean Squared Error

NB Narrowband

PESQ Perceptual Evaluation of Speech Quality

PI Packetization Interval

PLC Packet Loss Concealment

PSTN Public Switched Telephone Network

QoS Quality of Service

RTCP Real-time Trasport Control Protocol

RTP Real-Time Transport Protocol

SIP Session Initiation protocol

UDP User Datagram Protocol

UMTS Universal Mobile Telecommunication System

VAD Voice Activity Detection

VoIP Voice over Internet Protocol

WB Wideband

WLAN Wireless Local Area Network

Abstract

Telecommunications technologies are evolving at a rapid pace. The old Public Switched Telephone Network (PSTN) is being replaced with wireless and voice over IP (VoIP) systems. This requires the service providers to offer their services on competitive prices, on one hand, and to ensure the interoperability of their services over heterogeneous networks on the other. Added to this is the challenge of keeping up with the expectations of the clientele as regards quality of service (QoS). Thus to enable the successful deployment and functioning of a telecommunications network, it is equally important to estimate the speech quality as it may be perceived by the humans.

Speech quality is a subjective opinion, based on the human users' experience of a call. Recently, objective speech quality assessment has become a very active research area. This is an attempt to circumvent the limitations of subjective analysis by simulating the opinions of human testers algorithmically. There are two distinct approaches to objective testing namely, intrusive and non-intrusive. While intrusive techniques employ a reference speech signal to estimate the quality of a degraded one, the non-intrusive models do not enjoy this privilege as they rely solely on features of the signal under test.

The goal of this research was to derive superior non-intrusive speech quality estimation models. Model superiority was sought in a multi-objective sense: 1) enhancement of prediction accuracy of the derived models as compared to the previous ones. 2) model simplicity or parsimony was desired as it may enhance the computational efficiency. In this research this is achieved by employing a novel approach based on Genetic Programming (GP).

GP is a machine learning algorithm which coarsely emulates concepts adopted from natural evolution to automatically generate computer programs. Evolution is performed in the hope of finding a program or a symbolic expression that appropriately solves the problem under consideration. This potential benefit of benefit of GP has been utilized in this thesis.

Acknowledgements

First of all I would like to thank my PhD supervisor, Dr. Colin Flanagan, for his valuable advice during my doctoral studies. His brilliant engineering acumen is commendable. He always provided inspiring ideas and enlightening feedback.

I am thankful to the higher education commission of Pakistan and wireless access research centre, university of Limerick, for funding my research.

From among my friends I would specially like to thank Saleem-ullah Khan Khosa, as he had been a great source of inspiration for me during my undergraduate studies. Kashif Amin, a close comrade, always helped me in times of despair. The listening ability of Aimal Rextin is commendable as he would steadfastly lend his ears during melancholic moments of PhD studies.

I befriended Istvan Matyasovszki at the start of my PhD studies while he was already working for his PhD with Dr. Colin Flanagan. I must admit that I have rarely ever met a person of his attitude and personality. A thorough gentleman at heart and soul, he helped me a lot during my studies. Had he not been around, I could have had serious problems in my studies. He motivated me a lot and gave valuable suggestions as regards various aspects of research. Together we had a great time while discussing various co-curricular aspects of life such as politics, religion and entertainment. Meeting him remains one of the most enlightening experiences of life.

I am thankful to Dr. Atif Azad, my cousin, friend and a colleague, for providing valuable critique on our research. Atif and Dr. Conor Ryan were two main collaborators of the research presented in this thesis.

From among my past teachers I am indebted to Professor Faiz-ul-Hasan. He taught us physical metallurgy during the undergraduate years. He had an innate ability to explain difficult concepts in an easy to understand manner. From him I learnt how to think. After all these years I still find him unequivocal for his pedagogy skills. I was also highly inspired by the personalities Dr. M. A. Maud and Dr. Tariq Jadoon.

I must acknowledge that I inherited much of my engineering acumen from my uncle, Raja Iftikhar Mujtaba. I learnt a great deal about life by observing my uncle, lieutenant colonel (retired) Javed Mujtaba. I am thankful to my elder brother Kashif

Azad, he has always been around to utter a word of motivation during tough times of life. I am indebted to my other brothers, Mamoon, Asif, Qasim, Ali and Abdullah. I am thankful to my sister, Saira, as she has had to listen to me a lot during the past three years. I cannot truly acknowledge the support my parents have given to me in life. Father would set the *hard targets* and provide financial assistance. Mother would stick around during the course of journey to whisper motivation in my ears. It has always been my parents heartiest desire to raise their children as educated and well groomed adults. They sent us to the best schools which is a difficult thing to do in country like Pakistan. I am thankful to Abdul-Rehman for being around.

In the end I would also like to acknowledge that I truly enjoyed my stay in Ireland in general and university of Limerick in particular. It gave me a lot of self confidence while working here. I must say that I probably spent the best days of my life in Ireland.

Limerick, Ireland — Muhammad Adil Raja
Date June 2008

> "The Sciences do not try to explain, they hardly even try to interpret, they mainly make models. By a model is meant a mathematical construct which, with the addition of certain verbal interpretations, describes observed phenomena. The justification of such a mathematical construct is solely and precisely that it is expected to work."

– John Von Neumann.

Chapter 1

Introduction

The emergence of the Internet has been instrumental in changing the manner in which humans communicate today. The public switched telephone network (PSTN) is largely being replaced by wireless and Voice over Internet Protocol (VoIP) networks [Minoli and Minoli, 1998]. Moreover, the circuit switched wireless networks, such as GSM, are also being overridden by the doctrine of packet based communication by adapting to VoIP. Due to this, an increasingly heterogeneous environment has arisen where various network technologies are compelled to interwork in order for human speech communication to transpire successfully. The quality of speech suffers from various degradations as the speech signal traverses from one point of the network to the other. Various factors play a role in this, ranging from the terminal equipment employed for telephony, to the nature of devices responsible for routing the speech signal from one communication endpoint to another. Identifying the root cause of speech quality problems is a challenging task. The evaluation of speech quality is, thus, critically important. Speech quality estimation models serve as instruments for proper network planning, design, development, monitoring and also for improvement of quality of service (QoS).

Internet enables the concurrent transmission of various types of data traffic including text, video, audio and voice. Voice communication over the Internet is cost

effective in the sense that the relevant protocols tend to exploit the bandwidth redundancy that may exist on various paths or links between IP communication endpoints. However, the reduced cost comes with a degradation of quality. Quality of VoIP suffers because the existing IP network architecture was not designed for applications with stringent real-time transmission requirements. Large end-to-end transportation delays, variability in delay and packet loss may hamper smoothness of conversation between users. Moreover, in a heterogeneous environment speech quality may suffer from other distortions due to the use of different codecs, wireless transmission errors and transmission over wired/wireless links.

This thesis proposes non-intrusive speech quality estimation models for VoIP. Currently a number of such models exist in the literature. The objective here is to derive models with better accuracy in predicting the speech quality. A secondary objective is that the derived models be amenable to real-time evaluation of call quality.

1.1 Motivation

Non-intrusive models have some conspicuous peculiarities due to which they may be favored for speech quality estimation. There are two types of non-intrusive speech quality estimation models, namely, parametric and signal-based. VoIP quality estimation is normally done using a parametric model. The reason is that VoIP is affected more than anything else by the characteristics of IP network traffic, and that, the traffic parameters can be measured conveniently at an intermediate point on the network. Due to low computational requirements involved in gathering network traffic statistics, parametric models are also eminent for live and real-time quality estimation of a large number of calls concurrently.

It may also be argued that signal-based models are not suitable for quality estimation of VoIP. Firstly, because this latter class of models pays little, if any, attention

to IP traffic characteristics. Secondly, due to the compute intensive signal processing algorithms involved in the analysis of speech signal under test, such models are not deemed acquiescent for real-time evaluation of speech quality.

In an all *wired-IP* environment, where everyone uses VoIP over wired links, parametric models may be thought to be the most cogent choice of network planners and service providers. But in a heterogeneous environment where VoIP is expected to co-exist and co-operate with other technologies, such as circuit-switched wireless, VoIP over WLANs and PSTN, the speech signal is prone to other distortions apart from those characteristic of IP network traffic that may be apprehended only by a signal-based model. This fact alone advocates the need to develop effective signal-based models, alongside the development of more efficient parametric ones, and to develop hybrid models that retain the best elements of parametric and signal based models to give better estimates of speech quality.

This research has sought to derive more accurate and efficient models for speech quality estimation. Equal emphasis is placed on the development of parametric and signal based models.

1.2 Research Goals

Formally, this research seeks to pursue the following research goals:

- Derivation of a relationship between perceived speech quality and network traffic parameters, such as packet loss rate, burstiness in packet loss, jitter, packetization interval (payload size of a VoIP packet), frame duration and codec type etc.

  To this end, a significance analysis of each of these parameters is done to assay the impact of each of these parameters on speech quality. The impact of each of

these quality affecting parameters is analyzed using the state-of-the-art ITU-T P.862 algorithm [ITU-T, 2001b]. Alternative *parsimonious* models for real-time evaluation of the call quality are proposed as significant deliverables of this research.

- Analysis of the effect of each of these quality affecting parameters on speech quality in a *mixed* context (where both narrowband (NB) and wideband (WB) speech coding technologies may be present). This aims to propose a quality estimation model to cope up with the growing trend in VoIP communication technology to adapt to WB speech transmission, whereas the existing NB speech transmission is expected to prevail alongside during this transition.

  To this aim, effective equipment impairment factors are derived for the ITU-T G.107 (E-Model) [ITU-T, 2005a] that outperform the existing formulation for equipment impairment factors in terms of prediction accuracy. The wideband version of the ITU-T PESQ algorithm [ITU-T, 2005f] has been used as a reference.

- Derivation of a signal based speech quality estimation model that may have a better prediction accuracy than the existing models, and that may also be simple both in terms of implementation detail and computational requirements.

  To this end, a new model has been proposed by using the ITU-T P.563 [ITU-T, 2005d] algorithm as a speech feature extraction algorithm. The resulting model is a function of a reduced set of ITU-T P.563 features and has a better prediction accuracy than its reference implementation.

1.3 Algorithms for Model Derivation

Derivation of speech quality estimation models has been addressed from a numerical optimization perspective. Here two evolutionary algorithms namely, Genetic Algorithms (GAs) [Goldberg, 1989] and Genetic Programming (GP) [Koza, 1992] have been employed throughout the research for automatic derivation of non-intrusive models.

GAs and GP are machine learning techniques inspired by Darwinian evolution. GAs are counterparts of numerical optimization algorithms, where an objective function is pre-specified. GP makes no such assumption and finds the structure of the model as well in addition to the numerical coefficients with the sole of aim of optimizing an error metric. While traditional GAs evolve *coefficient arrays* that optimize the stated objective function, GP aims even higher; it seeks to find a suitably parameterised function that approximates the optimal mapping between the domain and the output variables.

Given a problem setting, evolutionary algorithms can potentially search for a globally optimum solution as opposed to getting stuck in local minima as in various other optimization algorithms used in machine learning [Koza, 1992]. This is attributed to an evolutionary process driven by stochastic changes in the *genomes* of a population's individuals. While traditional GAs are known for parameter optimization of a given mathematical model, GP is celebrated for sculpting mathematical expressions with desirable features. In the process of doing so, GP is also known to discard redundant data attributes [Langdon and Buxton, 2004].

1.4 Structure of The Thesis

This thesis is composed of eight chapters. Chapter 2 gives an introduction to VoIP. Various aspects of this technology are discussed. A detailed account is given of the various types of distortions that may be incurred by the speech signal as it traverses one part of the network to the other. These include both those that are typical of an IP network and those which are typical of a circuit switched or a heterogeneous network environment.

Chapter 3 gives an introduction to speech quality assessment. First, the subjective assessment methodology is discussed with an emphasis on the need for this type of assessment. This is followed by discussion on various types of objective speech quality estimation.

Chapter 4 gives an introduction to GP. Here an approach amenable to understanding by a non-specialist audience is adapted while not shying away from its most important aspects concerning numerical optimization and symbolic regression.

Chapter 5 details significant work done to derive parametric models to approximate human assessment of speech quality. Models are proposed that approximate the PESQ algorithm [ITU-T, 2001b] to a high accuracy and outperform the ITU-T P.563 algorithm [ITU-T, 2005d]. The models are designed to operate in an NB context.

Chapter 6 presents equipment impairment factors for estimation of the quality degradation caused by various NB and WB speech codecs along with IP network traffic parameters. It is shown that how the equipment impairment factors obtained by GP are superior to those obtained by the traditional E-Model formulation by using a systematic comparison between the prediction accuracies of the latter for a wide range of network distortion conditions. The WB version of ITU-T P.862 [ITU-T, 2005f] is used in this research.

Chapter 7 proposes a signal based model. The model is a function of a reduced

feature set of the ITU-T P.563 algorithm and performs better than the reference implementation of the latter.

Chapter 8 presents the conclusions along with the achievements of this research and directions for future work.

Chapter 2

Voice over Internet Protocol (VoIP)

As opposed to traditional circuit switched telephony, in VoIP the routing of voice conversations takes place over the Internet or an IP based network in the form of packets [Minoli and Minoli, 1998]. VoIP is cost effective in the sense that redundant resources of an already deployed Internet are used for transportation of voice. In traditional circuit switched telephony such as PSTN or ISDN a physical connection is first established between the participants of a call and it is retained for the whole duration of the call. The same is true of wireless mobile technologies such as GSM. In contrast, no such physical connection is established in VoIP. Voice packets are forwarded through a connectionless transport medium whereby they are expected to reach the destination. However, this is dependent upon availability of network resources. Despite the various benefits of VoIP communication, the technology has numerous limitations in terms of its impact on speech quality as perceived by the end user. These can be alluded to the manner in which the communication system affects the transmission of voice conversations. In what follows, the salient components of VoIP systems are discussed in detail. The effects of these components on speech quality are also discussed.

2.1 VoIP Transport

During a VoIP call the analog acoustic signal, composed and delivered by the vocal production system of a human speaker, is first converted to its digital representation. Once digitized, human speech is compressed by using a suitable encoding algorithm. After encoding into a suitable format the speech frames are packetized and sent to the receiver. End-to-end delivery of VoIP data is expected to meet certain minimum *real-time* constraints. For this purpose, services of *Real-time Transport Protocol* (RTP) [Schulzrinne et al., 2003] are used. RTP has been designed and optimized for transport of real-time traffic, unlike legacy transport protocols such as UDP or TCP. The services of RTP include payload identification, sequence numbering, timestamping and monitoring of end-to-end delivery of packets. Figure 2.1 shows the format of RTP header. RTP may also be used to distribute multimedia traffic to multiple recipients simultaneously if the underlying network has multicasting capability. However, RTP cannot operate on its own and is normally run over UDP to utilize its multiplexing services and checksum capabilities [Davidson et al., 2006, pp-22]. An RTP encoded payload has a 40-octect header. RFC 2508 [Casner and Jacobson, 1999] enables the compression of this header information to 2 to 4 octects on a hop-by-hop basis.

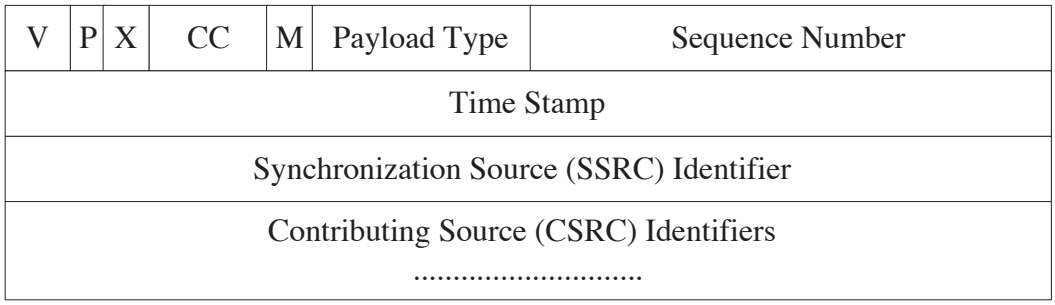


Figure 2.1: RTP Header

The receiver processes the packets and presents them to the playout (dejittering) buffer which is a temporary storage that aims to accumulate enough packets so that they can be played out to the listener as a steady stream as opposed to fragmented clips of voice. After the playout buffer the speech frames are decoded and in doing so any lost frames may be camouflaged by the decoder using a suitable packet loss concealment (PLC) algorithm. Finally the decoded signal is translated to its acoustic representation. Figure 2.2 shows the steps required for mouth-to-ear transportation of voice over an IP network.

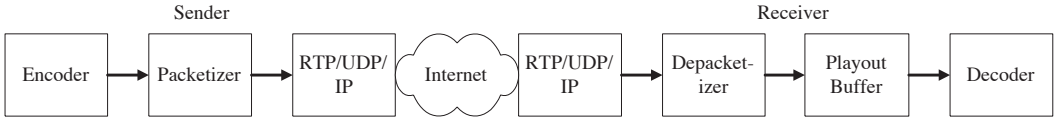


Figure 2.2: Conceptual Diagram of a VoIP Communication System

RTP is supplemented with its companion *Real-time Transport Control Protocol* (RTCP) [Schulzrinne et al., 2003]. RTCP report packets are used to communicate between the sources and destinations to maintain the *state* information of a conversation. The primary function of these reports is to provide feedback on the quality of the data distribution. This may be useful in meeting various QoS related objectives. RTP can further be supplemented with an RTCP-*extended report* (RTCP-XR) [Friedman et al., 2003]. Various RTCP-XRs may be used to convey more detailed statistics for VoIP monitoring.

2.2 Speech Coding

Speech codecs (coders/decoders) differ from each other in terms of features such as encoding bit-rate (kbps), algorithmic delay (ms), complexity and speech quality they may offer. Speech codecs employ various acoustic processing principles and techniques

to meet the listeners' expectation of perceived speech quality. In terms of encoding principles, speech codecs may be divided into two main categories; waveform and parametric. Each one of these is discussed briefly in the following sections.

2.2.1 Waveform Codecs

Waveform coding methods relate to the time domain representation of the speech signal. ITU-T G.711 [ITU-T, 1988b] is a primitive codec in this category. It gives a transmission bit-rate of 64 kbps with a sampling rate of 8 kHz. It has two modes of operation; A-law is used in Europe and μ-law is used in United States and Japan. Waveform codecs also employ differential coding principles, where a given coded sample produced by the coder is a function of the current input sample of the speech signal and the past n output samples of the coder. Transmitting the difference signal saves bandwidth, as the average difference between the samples is smaller than their actual amplitudes. Some examples of the differential coders include ITU-T G.726 [ITU-T, 1990a] and G.727 [ITU-T, 1990b].

2.2.2 Parametric Codecs

As opposed to waveform codecs, parametric codecs model the human vocal production system, and attempt to extract a reduced set of parameters relevant to the speech signal to be coded [Chu, 2003]. In doing so parametric codecs attempt to produce codes of minimum data rate by exploiting the *resonant* characteristics of the human vocal tract. The slow rate of change of signals originating in the vocal tract justifies this approach. Thus, a small set of parameters is used to approximate the signal in approximately a 30 ms wide window, during which the signal may be assumed to be stationary. These parameters include the following:

- Up to a dozen coefficients that define the resonant frequencies of the vocal tract.

- A binary indicator describing whether the excitation source (vocal cords) is *voiced* or *unvoiced*.
- A value for the *excitation energy*.
- In case of a voiced signal, a value for *pitch* is also included.

Together, these parameters constitute a *data frame*. The state of the speech waveform is approximated in this way by analyzing the speech waveform every 10 to 30 ms. Parametric codecs typically use *linear predictive coding (LPC)* [Makhoul, 1975] for optimization and computation of these parameters.

At the receiving side a corresponding decoder performs a synthesis operation on these parameters to reproduce the original waveform. Data rates of parametric codecs vary between 1.2 to 8 kbps for NB codecs. The rate depends on various factors that include frame rate, the number of parameters in the frame and the accuracy with which each parameter is coded.

Some examples from this family of codecs include ITU-T G.729 [ITU-T, 1996a], ITU-T G.723.1 [ITU-T, 1996b], *Adaptive Multirate Coding (AMR)* [ETSI, 2000]. These codecs have also been utilized in this research.

2.2.3 Wideband Codecs

Speech codecs may also be categorized in terms of their audio transmission bandwidth i.e. narrowband (NB) or wideband (WB). All the codecs listed in the previous section belong to the NB type. In NB the audio transmission bandwidth is restricted between 200-3400 kHz typically. In WB this is increased to 100-7000 kHz. It is believed that WB codecs may enhance speech quality as they make the speech sound more natural to human ears. Examples include ITU-T G.722 [ITU-T, 1988a], G.722.1 [ITU-T, 2005b], G.722.2 [ITU-T, 2003d] and G.729.1 [ITU-T, 2006a].

2.2.4 Auxiliary Components

Apart from mere encoding and decoding of the speech, sophisticated codecs of the present day are also equipped with auxiliary components that aim to enhance the perceptual quality of speech. For instance, in order to regulate the input and the gain of the output signal a codec may be equipped with an automatic gain controller (AGC) [Chu, 2003, pp-319]. Similarly, background noise degrades the quality of the speech signal. In order to alleviate this issue, a noise suppression or speech enhancement algorithm may be applied to the speech signal [Diethorn, 1997]. Other significant elements are silence suppression, dejittering buffer and packet loss concealment. These are discussed separately in the following sections.

2.2.4.1 Silence Suppression

Silence suppression, or discontinuous transmission (DTX), may also be implemented in codecs whereby the periods of a conversation when a speaker is silent are not coded and consequently not transmitted. DTX is aimed at bandwidth saving. A voice activity detector (VAD) is used to implement DTX. A comfort noise signal may instead be inserted in to the VoIP stream during the silent intervals [Zopf, 2002].

The processing of the speech stream by the VAD algorithm may lead to a clearly audible distortion. This is attributed to the *front-end clipping* of the speech segments immediately following a silence interval, leading possibly to loss of information [Davidson et al., 2006, pp-157].

2.2.4.2 Dejittering Buffers

An IP network introduces a variation in delay (jitter) on packets. Network jitter is a result of queuing delay caused by the intermediate processing nodes (routers and switches) of an IP network. As a consequence the decoder on the receiving end

may not receive a steady stream of speech frames. In order to provide the listener with a continuous stream of speech, a VoIP application implements a dejittering buffer [Davidson et al., 2006, pp148-149]. A dejittering buffer conceals the network induced jitter by storing enough voice frames before presenting them to the decoder to allow them to be fed at a constant rate into the decoder. Packets that arrive before playout time are used to reconstruct a source signal. Packets that arrive after playout time are discarded as they are of no avail in reconstructing an uninterrupted signal. A secondary, but equally important, objective of a dejittering buffer is to reduce packet discards due to out-of-order arrivals. Thus, any such packets are reordered if they arrive before their playout times have elapsed.

Buffering of packets increases the end-to-end delay of a VoIP stream. If delay is large the user may loose interactivity with other participant(s) of the conversation. This adversely affects the conversational quality of speech, hence imposing a limit on the capacity of the dejittering buffer. Various adaptive dejittering buffering approaches have been proposed either to achieve a minimum end-to-end delay given a certain packet loss rate [Ramjee et al., 1994] [Moon et al., 1998] [Rosenberg et al., 2000] [Fujimoto et al., 2002] or to achieve a minimum rate of packet loss due to late arrivals [Ramjee et al., 1994]. However, this approach has recently been shown to be inappropriate as it does not correlate well to the perception of speech quality in a conversational sense [Sun and Ifeachor, 2006]. Lately there has been a growing interest in designing adaptive dejittering buffers that dynamically adjust to a suitable combination of values for end-to-end delay and loss rate in pursuit of delivering optimum speech quality, or conversely for achieving a minimum possible degradation in quality [Sun and Ifeachor, 2006].

2.2.4.3 Packet Loss Concealment

For numerous reasons, a certain proportion of VoIP packets inevitably get lost during transmission. To circumvent the adverse effects of packet loss on perceived quality, speech codecs are typically equipped with a suitable *Packet Loss Concealment* (PLC) algorithm.

PLC techniques may be sender based or receiver-based. In sender based PLC, the sending device transmits additional information regarding the contents of speech frames. In case of a packet loss this additional information is used to recover the contents of the lost packet. Sender based PLC strategies include retransmission, *Forward Error Correction* (FEC) [Rosenberg and Schulzrinne, 1999], frame interleaving [Ramsey, 1970] and low bit-rate redundancy [Perkins et al., 1997]. In general sender based techniques are not recommended to be used with interactive applications, such as VoIP, due to the imposed end-to-end delay [Perkins et al., 1998].

An alternative is to employ a suitable receiver based PLC technique. Such techniques are useful for concealing packet losses containing voice data ranging between 4 to 40 ms and remain inferior to sender based schemes in terms of concealing the losses. There are mainly three types of receiver based techniques:

- *Insertion techniques:* A packet is inserted in place of a lost packet. This could be a silence packet or a noise packet or a repetition of a previous packet.

- *Interpolation techniques:* A suitable pattern matching technique or an interpolation method is used to search for a suitable waveform segment for a lost packet based on the waveform of the neighboring (received) packet(s). Such schemes are harder to implement but give better performance than insertion based schemes. Waveform codecs like ITU-T G.711 [ITU-T, 1988b] use such schemes.

- *Regeneration techniques:* In such a scheme the encoder's state is restored by

relying on the parameters of the neighboring frame(s) of a lost one. Parametric codecs normally implement such schemes.

A detailed survey on various PLC schemes has been given by Perkins et al. in [Perkins et al., 1998].

2.3 VoIP Quality of Service (QoS)

ITU-T Recommendation E.800 [ITU-T, 1998d] defines QoS as follows:

> *"Quality of Service (QoS): The collective effect of service performance which determines the degree of satisfaction of a user of the service."*
>
> *– ITU-T Recommendation E.800*

To this aim, QoS provisioning is tantamount to collective optimization of the performance of various network components so as to enhance the perceived quality of VoIP. The traditional QoS mechanisms can be divided into two broad categories. The first one is based on a class based prioritization of packets such as differentiated services (DifServ) [Nichols et al., 1998]. DifServ uses the type of service (ToS) field of the IP packet header to distinguish the packets into 4 priority classes. Based on this, DifServ-enabled routers of an IP network take forwarding decisions in favor of the packets with higher priority marks. Another approach is flow-based QoS provisioning in which traffic of a certain service may be associated with a particular network flow. The flow is treated in the network according to its priority e.g., resource reservation agreement. Examples of this include *resource reservation protocol (RSVP)* [Braden et al., 1997] and *multi protocol label switching (MPLS)* [Rosen et al., 2001].

A recent approach is based on application level control of the transmission of VoIP calls. In this a VoIP application adapts its configuration according to the operating

state of the network. Recently a perception based notion of QoS assessment has also been adopted. According to this quality of speech, as perceived by the user of a VoIP call, reflects upon the QoS level of the network. Feedback from the users' experience of VoIP is used to address the issues relevant to end-to-end delay, jitter and packet loss. Operating conditions of the VoIP application such as codec bit-rate, or capacity of dejittering buffer are adapted to provide best possible quality to the user. Examples of this include [Sun and Ifeachor, 2006] [Narbutt and Davis, 2005] [Hoene et al., 2005].

Apart from successful network operation and support for VoIP, issues related to network security also fall under the umbrella of QoS provisioning. These may include unauthorized monitoring, eavesdropping, misuse, human error and natural disaster etc. QoS shall not be discussed further since it is beyond the scope of this dissertation.

2.4 Speech Quality Impairments

This section describes the various kinds and sources of impairments that may lead to a degradation of speech quality of VoIP. Special emphasis is laid on those impairments that deteriorate the quality of speech in a *listening only* scenario, albeit other scenarios exist.

2.4.1 Packet Loss

A cardinal metric that affects VoIP quality is network packet loss. VoIP undergoes packet loss due to the nature of the underlying packet switching network. It may occur due to reasons such as link failures, network congestion, irredeemable errors in packets and jitter buffer packet overflow. An additional reason can be excessive delay that is incommensurate with the play-out deadline of a packet or a frame. In wireless networks packet loss may also occur due to ambient interference on the radio

link that may result in bit errors. The issue of bit errors and their effect on packet loss is discussed in more detail in section 2.4.3. The degree of impairment associated with packet loss may be characterized with the distribution of packet loss, packet size and the type of method applied for packet loss recovery. Packet loss distribution is discussed in more detail below.

2.4.1.1 Packet Loss Distribution

In the literature [Raake, 2006], the behavior of packet loss has been modeled using a number of statistical distributions depending on the packet loss pattern. A given packet loss pattern may in turn depend on the nature and operating conditions of the underlying network. Packet loss is commonly assumed to follow a Bernoulli-like distribution. This is also referred to as a *random* distribution in the literature [Raake, 2006, pp-63]. Packet loss may exhibit temporal dependency too [Jiang and Schulzrinne, 2000]. This implies that the loss of a single VoIP packet may lead to the loss of immediately succeeding packets. This phenomenon leads to burstiness in the behavior of packet loss.

More formally, burstiness implies that the loss of a certain packet depends on the loss or reception of previous packet(s). A two state Markov chain has been proposed by several authors to capture this temporal dependency e.g. [Bolot, 1993], [Sanneck and Carle, 2000]. Each state of such a Markov model is used to depict a loss and a no-loss scenario respectively. Figure 2.3 shows this model, where p is the conditional probability of losing the packet numbered $n+1$ given that the n^{th} packet is successfully received. Similarly, q is the conditional probability of receiving the packet numbered $n+1$ given that the n^{th} packet was lost. $1-q$ corresponds to the conditional loss probability (clp). This model reduces to a Bernoulli model if $p = 1-q$. Usually $p < 1-q$. This means that the probability of losing a packet numbered $n+1$ is higher when the n^{th} packet is already lost as compared to the case when the n^{th} packet

is successfully received. This condition models the bursty behavior in a meaningful sense. Equation (2.4.1) corresponds to the mean loss rate (mlr) and is also known as the unconditional loss probability (ulp).

$$mlr = ulp = \frac{p}{p+q} \tag{2.4.1}$$

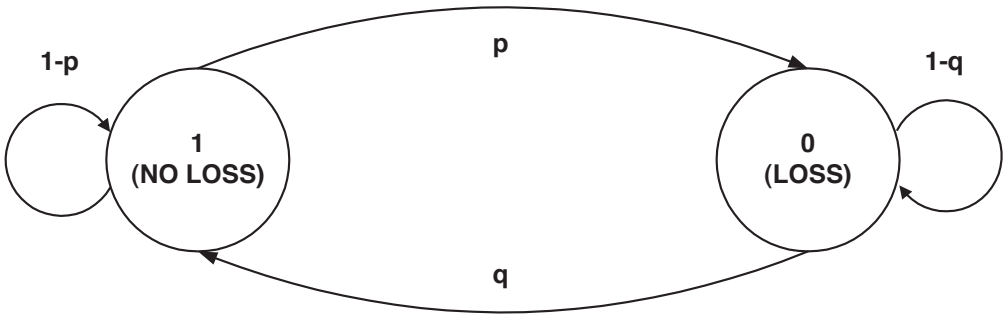


Figure 2.3: The 2-state Markov chain for modeling bursty packet losses

The burst and gap lengths (loss and no-loss runs) are geometrically distributed random variables. mbl and mgl in (2.4.2) correspond to the means of the geometrically distributed burst and gap lengths respectively [Sanneck and Carle, 2000] [Zwillinger, 2003].

$$mbl = 1/q, \quad mgl = 1/p \tag{2.4.2}$$

The values of p and q can be calculated from a network trace using gap and burst length distribution statistics according to [Jiang and Schulzrinne, 2000], [Sanneck and Carle, 2000]. The number of gaps having lengths i ($i = 1, 2, ..., n-1$) is denoted by g_i, where $n-1$ is the length of the longest gap received. In a similar way the number of bursts having lengths i ($i = 1, 2, ..., m-1$) is denoted by b_i, where $m-1$ is the length of the longest burst. Using the values of g_i and b_i the values of p and q can be

calculated in accord with (2.4.3) and (2.4.4).

$$p = 1 - \left(\sum_{i=2}^{n-1} g_i . (i-1) \right) / \left(\sum_{i=1}^{n-1} g_i . i \right) \tag{2.4.3}$$

$$q = 1 - \left(\sum_{i=2}^{m-1} b_i . (i-1) \right) / \left(\sum_{i=1}^{m-1} b_i . i \right) \tag{2.4.4}$$

Extended versions of the 2-state model are the *Gilbert model* [1] and the *Gilbert-Elliot model*.

In order to accurately model the packet loss of up to n consecutively lost packets, n-state models have been proposed separately by Sanneck and Carle [Sanneck and Carle, 2000] and Yajnik et al. [Yajnik et al., 1999]. Such approaches are considered favorable for capturing long term dependencies of packet loss. However, the modeling process may become formidable for large n. In [Clark, 2001] Clark proposed a simplified approach based on a 4-state Markov model still capable for capturing longer term loss dependencies.

2.4.2 End-to-end Delay

End-to-end delay affects the interactivity of a VoIP conversation. It is composed of various components such as processing delay by the codec, transportation delay that may be incurred by the underlying IP network, delay induced by the dejittering buffer, and other signal processing components such as echo cancellers. Various components of the network that may cause delay are listed in Table 2.1 along with the associated values for delay.

ITU-T Recommendation G.114 [ITU-T, 2003c] provides guidance on the effect of end-to-end one-way delay. According to this it is desirable to achieve an end-to-end

[1] The 2-state Markov model discussed above is frequently referred to as the Gilbert model in literature, which is a misnomer.

Table 2.1: Various sources of delay with corresponding values

Delay Source	**Typical Range (ms)**
Encoding	15–30
IP Network	70–120
Dejittering Buffer	50–200
Decoder	10–20
Total	165–400

delay of less than 150 ms. However, regardless of the type of application, delay should not exceed more than 400 ms.

As the focus of this thesis is on estimating *listening quality* of speech, end-to-end delay and its effect shall not be discussed further in this thesis.

2.4.3 Bit Errors

Bit errors may occur in certain wireline and wireless communication technologies. Wireless networks are more prone to bit-errors due to ambient interference on the radio link. As VoIP is based on packet based communication, bit-errors are largely taken care of by the UDP checksum. The checksum mechanism guards against any violations in the UDP header as well as in the UDP payload by dropping packets with incoherent checksums. Thus, flipping of even a single bit may have a considerable effect on quality as it results in the loss of the whole VoIP packet. Consequently this approach may lead to deterioration of quality as it does not allow for recovery techniques to be applied to the speech frames. For instance, modern codecs, such as GSM-FR and AMR-NB [ETSI, 2000], implement frame recovery mechanisms whereby frame bits are classified according to their perceptual relevance, thus, allowing frames to be dropped only when the most perceptually relevant bits are flipped during transmission, and professing recovery otherwise. Implementation of this approach requires one to disable the UDP checksums on the payload. In [Hammer et al., 2003] Hammer et al. showed that by retaining and decoding VoIP frames with bit errors rates in the

range of 10^{-5}–10^{-3} may result in a higher speech quality as compared to the scenario when the erroneous speech frames are dropped.

2.4.4 Noise

A VoIP stream undergoes distortion due to noise from various sources. Firstly, noise may be introduced due to codecs. Waveform codecs introduce signal-correlated noise to the speech signal due to quantization. This noise is multiplicative in nature as it is a function of the amplitude of the speech signal.

In the case that a codec implements a VAD algorithm, it may insert comfort noise into the outgoing VoIP stream [Zopf, 2002]. Comfort noise may lead to a clearly audible distortion as it is perceptually different from the actual speech signal and the background noise at the sending side [Raake, 2006, pp-84].

Ambient noise at both send and receive sides may also lead to considerable difficulties in conducting telephonic conversations. Background noise at the send side is usually suppressed using a noise suppression or a speech enhancement algorithm.

2.4.5 Impairments due to Transcoding

Often participants of a call may not have similar codecs deployed on their telephony equipment. An example of this is when one of the participants may be using VoIP with ITU-T G.723.1 as the preferred codec, whereas the other participant may be using PSTN, which uses ITU-T G.711. In this situation, in order to carry the speech of the sending participant to the recipient, encoded speech would have to be converted to a format amenable for processing by the codec implemented on the latter's telephony equipment. A similar phenomenon, termed as *tandeming*, is ubiquitous in wireless networks for similar reasons, where the speech signal traverses a *tandem* of codecs on its way to the intended recipient. Transcoding results in further degradation of the

speech quality compared to the cases where a single codec is used by both participants of the call. It is reported by Campos Neto and Corcoran in [Neto et al., 1999] that mean opinion score (MOS)[2] may drop by more than 0.5 in the single tandem case i.e., where speech is transcoded only once. Clearly, encoding and decoding the speech signal multiple times has adverse effects on the quality of the output signal. A notable effect of transcoding is that the quality degradation observed when the speech signal traverses the network in one direction is not the same as if it were to traverse the network in the opposite direction. This is to say that in a tandem of two codecs, namely 'X' and 'Y', the quality degradation when the signal traverses the two codecs in the order 'X→Y' is not the same as when it were to traverse them in the order 'Y→X'. This asymmetry of distortions, as also reported in [Möller et al., 2006], is a cause of numerous complications in speech quality estimation.

2.4.6 Miscellaneous Impairments

Various other important impairments or sources of impairments exist in a VoIP network. Some of these are briefly described below.

Talker echo is a reflection of the talker's own speech from a certain point in the communication path. It occurs when the delay of the reflected speech signal exceeds a certain threshold. In that case the reflected signal signal affects the interactivity of the conversation. It is specifically important in situations where the network delay may be considerable e.g. VoIP. Listener echo occurs as a result of multiple reflections of a transmitted speech signal. The reflections may arise due to room acoustics at the send side, or the user interfaces. *Loudness* and talker's *sidetone* are other crucial factors affecting quality perception. A detailed account of various impairments can be found in [Raake, 2006].

[2]MOS terminology is explained in chapter 3

2.5 Conclusion

This chapter presented an introduction to VoIP, its various components, and the associated factors that may affect speech quality. This thesis is focused on *listening* quality of speech; the quality of speech in a listening only context. Delay related impairments such as end-to-end delay and echo shall not be discussed further as they affect the speech quality in a conversational scenario. The main impairments under discussion would be those related to packet loss and speech codecs.

Chapter 3

Approaches to Speech Quality Estimation

3.1 Introduction

Speech quality estimation is vital to the evaluation of QoS offered by any telecommunications network. Traditionally, speech quality is estimated using subjective tests. In subjective tests, the quality of a speech signal under test is evaluated by a group of human listeners who assign an opinion score on an integral scale ranging between 1 (bad) to 5 (excellent). The average of these scores, termed the *Mean Opinion Score (MOS)*, is considered as the ultimate determinant of the speech quality [ITU-T, 1996c]. Subjective tests are, however, time consuming, expensive and hard to conduct. Moreover, due to these reasons subjective tests are not easily repeatable; a feature that may be desirable during transmission planning as well as network monitoring. To make up for these limitations, there has been a growing interest in devising software based objective assessment models. There are two kinds of objective assessment models, namely, intrusive and non-intrusive. Intrusive models evaluate the quality of a distorted speech signal in the presence of a corresponding reference signal. The current

ITU-T recommendation P.862 (PESQ) [ITU-T, 2001b] is an example of such an approach. Non-intrusive models, on the other hand, do not enjoy this privilege and base their results solely on the *estimated* features of the signal under test. For this reason, the results of the latter type of models are generally considered inferior to those of the former.

Non-intrusive models can further be classified either as *signal-based* models or the *parametric* ones. As the name suggests, signal-based models are based on the digital signal processing of human speech. An example of such a model is the current, state-of-the-art, ITU-T Recommendation P.563 for *single-ended* estimation of speech quality [ITU-T, 2005d]. Parametric models, on the other hand, base their results on various properties relevant to the telecommunications network. In the case of Voice over IP (VoIP), these may be transport layer metrics such as packet loss, jitter and end-to-end delay of a call. Such models are deemed suitable for real-time evaluation of call quality. An example of a parametric model is the ITU-T G.107, commonly referred to as the E-model [ITU-T, 2005a]. Figure 3.1 shows a classification of various speech quality estimation methods.

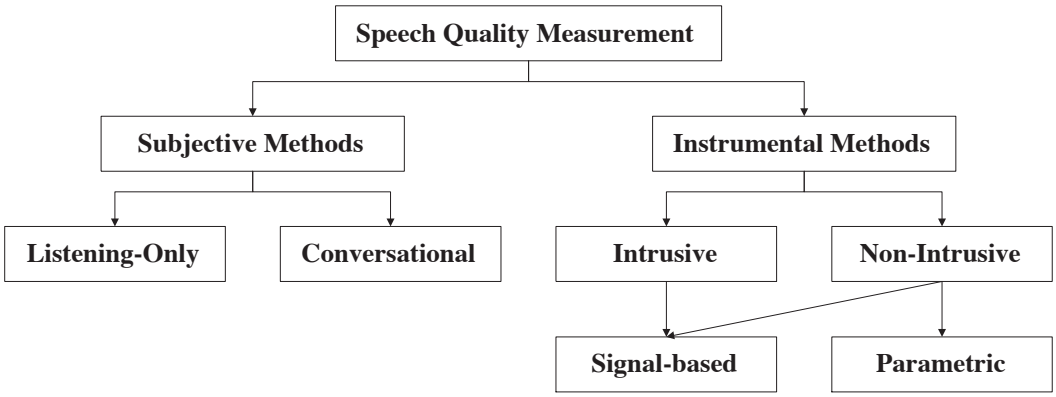


Figure 3.1: Various categories of speech quality assessment methods.

The rest of the Chapter is organized as follows. Section 3.2 discusses various

subjective methods for speech quality measurement. Section 3.3 discusses objective methods for speech quality estimation.

3.2 Subjective Methods

The term *subjective* refers to the methods that employ human users to comment on the quality of speech, without any aid or intervention of a computerized algorithm that may itself have a role to play in the assessment of speech quality. This definition of the term *subjective* has been considered as a misnomer according to Blauert [Blauert, 1997], as he states that quality opinions obtained through instrumental models are also subjective. To support his argument he suggests that as a human subject is behind the development of an instrumental model, the model imitates the human developer. Moreover, since it is the human who ultimately interprets the results of an instrumental model, the assessment procedure is subjective. In order to elucidate the usage of the term subjective, Raake [Raake, 2006, pp-24] has made use of the term *auditory methods* as the ones employing human subjects solely for assessment of speech quality. Where quality is analyzed by employing a software or mathematical model, the term *instrumental* is used as opposed to *objective*.

However, to keep in harmony with most of the literature on speech quality, the methods employing only humans for the assessment of speech quality are referred to as *subjective methods* in this dissertation. Any software based methods are referred to as *objective methods*; these include both intrusive and non-intrusive methods.

In [Jekosch, 2005, pp-91] Jekosch has given the following definition of a speech quality test:

> *"[a] routine procedure for examining one or more empirically restrictive quality features of perceived speech with the aim of making a quantitative statement on these features."*

Based on this definition Raake categorizes subjective tests methods either as utilitarian or analytical [Raake, 2006, pp-24]. According to this, a utilitarian method is one that focuses on measurement of a single perceived feature or integral quality of speech quality. An analytical method is one that investigates all or a subset of perceived features associated with quality. In other words, utilitarian methods employ a uni-dimensional quality rating scale. Analytical methods employ a multi-dimensional analysis so as to reveal and quantify various perceived features of the speech signal under test. In what follows, each of these methods is briefly described.

3.2.1 Utilitarian Methods

Utilitarian methods aim at a uni-dimensional analysis of the speech stimuli. Along with this, efficiency of test administration and data analysis and reliability of test method are also primary goals. The main utilitarian tests are as follows:

3.2.1.1 Listening Only Tests

Most utilitarian methods are conducted as listening only tests (LOTs). Listening tests vary from each other in terms of whether the test is conducted solely using the speech signals to be tested or if the evaluators are also presented reference signals corresponding to the various test stimuli. ITU-T Recommendation P.800 [ITU-T, 1996c] describes detailed procedures for conducting various types of listening tests. Each of these is discussed below briefly.

Absolute Category Rating Tests

Absolute Category Rating (ACR) tests are most popular in telecommunications for assessment of speech quality. ITU-T P.800 [ITU-T, 1996c] recommends various scales depending on the focus of the test. The five point integral scale is most commonly used and it is referred to as the *MOS* scale. This is depicted in Table 3.1. In

these tests a group of subjects (testers) evaluate a speech sample composed of 2–5 short, independent and meaningful sentences, not exceeding 10 s, using the 5-point scale. The opinions of each of these subjects are averaged to obtain the *mean* opinion score *(MOS)*.

Table 3.1: Five-point *MOS* scale

Score	**Interpretation**
5	excellent
4	good
3	fair
2	poor
1	bad

Degradation and Comparison Category Rating Tests

Degradation category rating (DCR) or comparison category rating (CCR) tests employ a paired comparison of speech samples. In DCR, a testing subject is first presented with a clean speech signal. This is followed by assessment of the actual, possibly degraded, speech signal. The subject is asked to rate the degradation of the second sample with respect to the first.

In CCR the subject is presented with a pair of test stimuli. The second stimulus is rated with reference to the first. Both stimuli are chosen randomly from a pool of test stimuli.

By employing a comparison based approach, DCR and CCR methods give insight into the speech quality with higher resolution. Both DCR and CCR also employ a 5-point category scale similar to the ACR tests. The details concerning these tests are also listed in ITU-T P.800 [ITU-T, 1996c].

Isopreference Tests

This method is somewhat similar to the DCR or CCR tests. In this test a pair of degraded and reference speech signals is presented to the listener for comparison. The listening based comparison is continued by repeatedly changing the degradation

level of the reference signal until it yields the same quality as that of the degraded signal. At this point, if a quantitative relation is known between the quality and the degradation of the reference signal, it is used as an estimate of speech quality [Raake, 2006, pp-28]. ITU-T Recommendation P.800 [ITU-T, 1996c] defines the *threshold method* which is closely related to this technique.

Continuous Evaluation

This method aims at addressing time varying degradations such as packet loss. It is similar to the ACR method in the sense that evaluation takes place without any reference signal. However, instead of a single quality estimate, the tester is asked to continuously evaluate the speech signal over its whole duration with the help of a slider; thus a continuous version of the 5-point rating scale of ACR method is employed. After the continuous judgement the tester is also asked to estimate the integral quality of the speech stimulus on ACR scale. This is used to make a relationship with the instantaneous and integral estimates of quality.

During tests, the instantaneous quality estimates are made at least after every half a second. The length of each stimulus may vary between 45–180 s. Both instantaneous ratings and integral quality estimates are averaged over subjects. This gives a mean instantaneous rating profile and an integral MOS. ITU-T P.880 [ITU-T, 2004] discusses continuous evaluation in more detail.

Third Party Listening Tests

These tests are listening tests but emulate conversation tests. A test subject is presented with a conversation between two speakers and is placed in the position of one of them. Thus, the tester does not talk himself, but passively participates in a conversational scenario. These tests are aimed at reducing the costs and efforts associated with data collection for conversational test scenarios at the expense of realism of a conversational scenario. ITU-T Recommendations P.831 [ITU-T, 1998c] and P.832 [ITU-T, 2000] discuss these tests in detail.

3.2.1.2 Talking and Listening Tests

These tests are closer to real conversational tests as opposed to the third party listening tests. In these tests the test subjects partake in conversation by listening and talking. Due to the active role of the test subjects these tests have been used for evaluation of echo cancelers [ITU-T, 1998c].

The realism of a conversation test is compromised due to the use of a Head and Torso Simulator (HATS), that is employed as a conversation partner of the test subject. A HATS is composed of an artificial head with ears, equipped with microphones, and an artificial mouth. The head is mounted on a dummy torso. The torso approximates the sound shadowing introduced by a real person [Raake, 2006, pp-29-30].

3.2.1.3 Conversation Tests

Conversation Tests (CTs) employ human test subjects for the assessment of speech quality. This method is superior to the other utilitarian methods due to this and numerous other reasons. However, CTs have limited usability due to time and effort required. Moreover, the tests cannot be repeated with the same degradation conditions and conversational scenarios. ITU-T P.800 [ITU-T, 1996c] lays the procedure for conducting CTs.

3.2.2 Analytical Methods

Speech quality is normally considered as a uni-dimensional entity. However, in certain scenarios it becomes incumbent on transmission planners to analyze various aspects of speech quality. Thus, a system engineer may be interested in finding out the effect of a codec on naturalness as well as on smoothness of speech. This leads to a requirement for multidimensional analysis of speech.

Analytical methods deal with identification and analysis of features that may affect

the perception of speech. This assumes that the perceived features have a correlation with the perceived quality of the test stimuli. Analytical methods employ adroit subjects who may distinguish between various features independent of their predilection for a few. The very nature of these methods suggests that speech quality or perception has multiple dimensions. Hence, these methods entail a multidimensional analysis. Analytical methods shall not be discussed further in this thesis. Thorough discussions on these methods can be found elsewhere in [Möller, 2000, Jekosch, 2005, Raake, 2006].

3.3 Objective Methods

Objective methods[1] for speech quality estimation have become popular in recent years. Objective methods aim at replacing human subjects with computational models for speech quality estimation. As a result, they provide a quick, cost effective and easily repeatable way of measuring speech quality. Objective methods normally output their results in the form of MOS. Thus, to differentiate between the results obtained by objective and subjective methods ITU-T P.800.1 [ITU-T, 2003b] has recommended a *mean opinion score terminology*. According to this, the MOS obtained by subjective tests are denoted by *MOS-LQS (MOS-listening quality subjective)* and MOS obtained by objective tests are denoted by *MOS-LQO (MOS-listening quality subjective)*. Objective methods can be subdivided into two categories; intrusive methods and non-intrusive ones. In what follows both types of methods are discussed briefly.

[1] Objective methods are also known as instrumental methods in literature.

3.3.1 Intrusive Methods

Intrusive models for speech quality estimation compare the speech signal under test with a reference signal, which is normally a clean, distortion free version of the signal under test. Intrusive models may be of two types depending upon the type of signal processing employed for quality estimation. The first type of models, and the earliest of all, employ time domain measures, such as signal to noise (SNR) ratio or segmental signal to noise ratio (SNR_{seg}) [Quackenbush et al., 1988]. Time domain models are simple to implement and lend themselves easily to understanding by humans. Such models are useful for estimating the performance of waveform codecs. However, modern low bit-rate codecs employ complex human vocal production models and do not render themselves to accurate analysis by time domain models. Such models are also prone to time domain misalignments between the test and the reference signals; slight misalignments may result in grossly erroneous estimates.

The second, and more sophisticated, type of models are based on *perceptual* domain measures of the human auditory system. So far such models have been most successful in estimating speech quality and have gained the widest popularity. Such models transform the time domain waveforms of test and reference speech signals into a perceptually relevant domain.

Some examples of perceptual speech quality estimation include:

- PESQ (Perceptual Evaluation of Speech Quality) ITU-T Recommendation P.862 [ITU-T, 2001b].
- PSQM (Perceptual Speech Quality Measure) ITU-T Recommendation P.861 [ITU-T, 1998b].
- MNB (Measuring Normalizing Blocks) [Voran, 1999a] [Voran, 1999b]

3.3.1.1 The PESQ Algorithm

The PESQ algorithm is the current standard for speech quality estimation. It inherits the psychoacoustic model of PSQM and the time alignment mechanism of *Perceptual Analysis Measurement System (PAMS)* proposed by Rix and Hollier [Rix, 2000] and Rix *et al.,* [Rix et al., 2002]. The general structure of PESQ algorithm is given in Figure 3.2. A textual description of the PESQ algorithm is as follows:

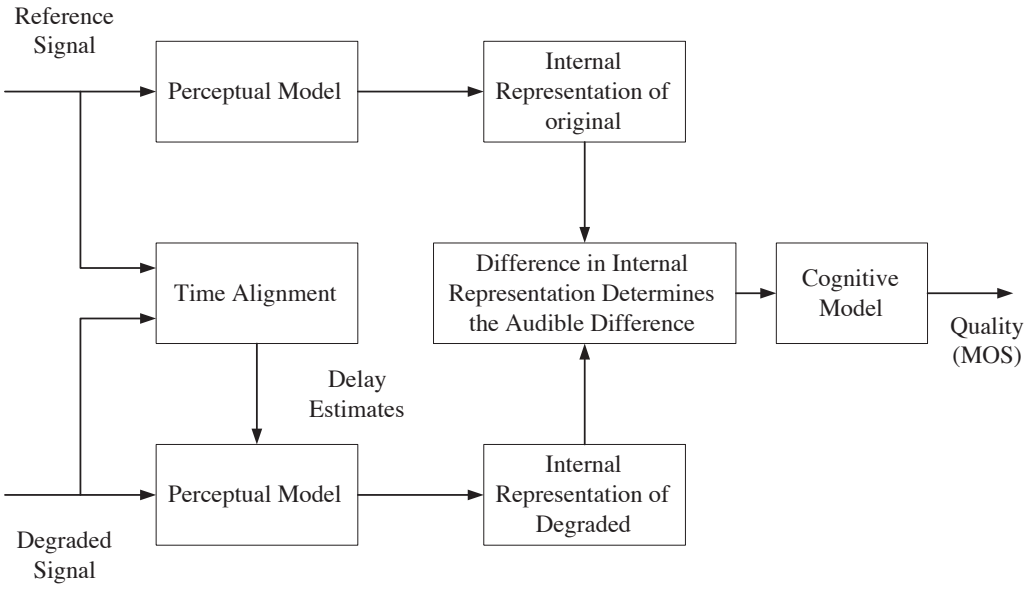


Figure 3.2: Intrusive speech quality estimation. Adapted from [ITU-T, 2001b]

1. Level alignment: Loudness levels of both distorted and reference signals are adapted.

2. Input filtering: The speech signals are treated with a filter that emulates the frequency response of the listening (receiving) end of a typical telephony handset. Such a filter is specified as the (modified) IRS receive filter in ITU-T Recommendation P.830 [ITU-T, 1996d].

3. Time alignment: The PESQ algorithm implements a complex time alignment

process. The time alignment computes time delay values and provides these to the perceptual model to allow for a comparison of the corresponding parts of the original and degraded speech signals. PESQ follows a multistage time alignment procedure listed in [Rix et al., 2002].

4. Time-frequency transformation: The signals are transformed from time domain to time-frequency domain using a short-time FFT. Signals are decomposed into 32 ms frames with 50% overlap. Hann window is applied. A frame size of 32 ms is chosen because this approximates the length of a typical *phoneme*. The start points of frames of the degraded signal are shifted according to the time delay information obtained from the time alignment module. The time axis of the original signal is kept unmodified. If the delay increases, parts of the degraded signal are discarded. In case if decrease in delay is observed, parts of the degraded signal are repeated.

5. Computation of pitch power densities: Frequency is converted from hertz (Hz) to Bark scale [Zwicker, 1961]. The Bark scale is a nonlinear frequency scale corresponding to the *critical bands* of hearing. A critical band refers to the frequency bandwidth of a filter. It is believed that auditory signal is warped in the human ear by a *band* of such filters, with center frequency spacings and bandwidths increasing with frequency. The resolution decreases with increasing frequencies in a nonlinear fashion. Thus, a Hz to Bark transformation is implemented by binning and summing the per frame FFT bands according to a variant of the Bark scale transformation followed by normalization of the sums. This results in pitch power densities of the reference and degraded signals.

6. Calculation of the loudness densities: The pitch power densities of original and degraded signals are transformed to a Sone loudness scale using Zwicker's law [ITU-T, 2001b]. The Sone loudness scale simulates the nonlinear relation between the intensity of sound and its loudness perceived by humans.

7. Computation of the disturbance density: The signed differences between

the loudness densities of the distorted and reference signals are computed. A positive difference, at any point, indicates the addition of other components, such as noise, to the signal. Whereas a negative difference indicates that (spectral) components have been omitted from the signal. These signed differences are stored in a 2-dimensional array forming a *raw* disturbance density in the time-frequency plane. Additional processing is applied to smooth the disturbance density. Specifically, masking by loud spectral components in each time-frequency cell is modeled.

8. Modeling of the asymmetry effect: The PESQ algorithm models the asymmetry effect [Beerends, 1995]. The asymmetry ensues from the fact that when a codec distorts a speech signal, it will generally be difficult to introduce a new component in the time-frequency plane that will smoothly integrate with the speech signal. This will result in a clearly audible distortion. If, on the other hand, a codec simply leaves out a spectral component, the distortion will be less objectionable. The asymmetry effect is modeled as a ratio between the distorted and the original pitch power densities. The result of this step is a 2-D array containing an asymmetrical disturbance density.

9. Aggregation of disturbance densities over frequency: The disturbance densities calculated in the last two steps are integrated over frequency for each frame. This results in two arrays of frame disturbances for corresponding densities.

10. Aggregation of disturbances over time: A two step aggregation of both disturbances is performed at this stage. The first is a split second aggregation in which disturbances corresponding to *phonemes* are aggregated for 20 successive frames. This results in two disturbance arrays corresponding to *syllables*. This aggregation is performed by employing L_6 norm. Next the values of these disturbance arrays are aggregated over the entire length of the speech signal using the L_2 norm.

11. Computation of the PESQ score: The output of the PESQ algorithm is a MOS score and it is a linear combination of the aggregated disturbance values

computed in the previous step. The linear combination was optimized for a large set of subjective experiments. At the time of its standardization, the results of PESQ algorithm had an average value of Pearson's product moment correlation coefficient [Walpole et al., 1998] equal to 0.935 for a large number of subjectively evaluated speech databases. Pearson's product moment correlation coefficient is normally used to assay the prediction accuracy of an instrument model, with a value closer to 1 implying a better correlation of the model's results with those of the subjective tests.

The PESQ algorithm outputs its results on the MOS scale and emulates ACR tests. The PESQ algorithm was modified and extended numerous times. ITU-T P.862.1 [ITU-T, 2003a] is currently the most up-to-date version. The PESQ algorithm was initially designed for NB speech quality estimation. ITU-T P.862.2 [ITU-T, 2005f] is a recent variant of the PESQ algorithm for speech quality estimation in a WB context.

3.3.2 Non-Intrusive Methods

Non-intrusive speech quality estimation is a challenging problem in the sense that a reference, or a clean, signal is not available to the computational model. Quality estimates are based solely on the speech signal under test, or on the knowledge of the system under test. Consequently, the results obtained by such models are also inferior to those of intrusive models. However, they can be significant for live and real-time evaluation of speech quality. These methods are also known as *no-reference* or *single-ended* methods. Non-intrusive methods of speech quality estimation may further be divided into two categories, namely parametric methods and signal-based methods. Figure 3.3 gives a pictorial representation of such models. A brief description of these methods is given in the following sections.

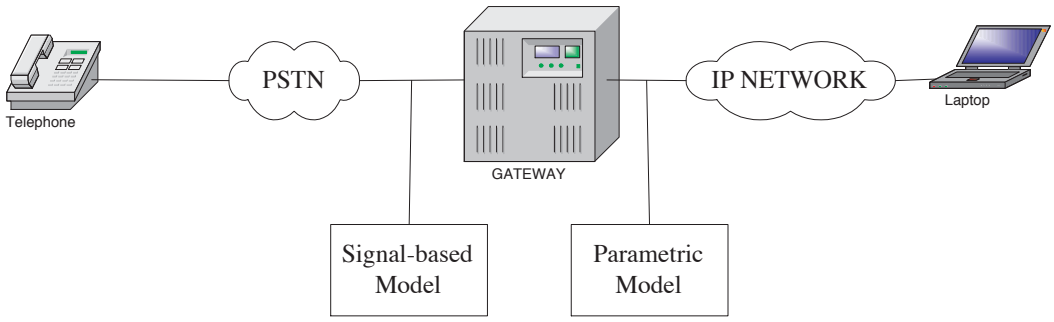


Figure 3.3: Non-intrusive Speech Quality Estimation Models.

3.3.2.1 Parametric Methods

Parametric methods estimate the speech quality by using instrumentally measurable characteristics of the communications network. In the case of VoIP these may be variables such as packet loss statistics, end-to-end delay and codec type. Normally the design goal is to approximate the subjective opinions of speech quality or the results of a superior intrusive method, such as the PESQ algorithm. Thus, it may be sought to maximize the *Pearson's product moment correlation coefficient* or to minimize mean squared error (MSE) [Walpole et al., 1998] between the MOS-LQO produced by the model under development and MOS-LQS for a possibly large number of training/testing instances. The degraded speech signal is itself not available to a parametric model. For this reason these methods require a complete characterization of the system under test. Consequently, these are also called *glass box* models [Rix et al., 2006]. A handful of models of this type exist which include both standardized as well as third-party algorithms. The most popular and widely used among these is the ITU-T Recommendation G.107 [ITU-T, 2005a], commonly referred to as the E-model. The E-model is based on an impairment factor principle according to which the collective effect of various impairments on speech quality is considered to be additive in nature. The output of the E-model is the *rating factor*, R. R ranges

between 0 (poor quality) to 100 (optimum quality). An invertible relationship exists between R and MOS. Three impairment factors are emphasized in the model. These include, impairments that occur simultaneously with the speech signal, impairments due to delay and impairments due to equipment such as packet loss and distortions due to low bit-rate coding. ITU-T has devised a method to derive equipment impairment factors for E-Model by using instrumental models such as PESQ [ITU-T, 2002]. E-model was designed for transmission planning purposes initially. However, now it is also being used in networks for on-line monitoring of speech quality [A. D. Clark, 1998]. E-model was originally developed for NB telephony. Currently its extension for WB telephony is under progress [Möller et al., 2006].

A number of other third party algorithms also exist. Sun and Ifeachor [Sun and Ifeachor, 2006] and Rosenbluth [Cole and Rosenbluth, 2001] have proposed logarithmic functions to compute impairment factors for the E-model. Sun and Ifeachor [Sun and Ifeachor, 2006] used the PESQ algorithm as a reference to compute equipment impairment functions.

In [Clark, 2001] Clark identified the *recency effect*. He stated that the impression of an impairment on human memory fades as time passes. He emulated this innate ability of humans to remember the effect of an impairment only for a certain amount of time.

Sun and Ifeachor [Sun and Ifeachor, 2002a] and Mohamed et al. [Mohamed et al., 2001, Mohamed et al., 2004] separately derived parametric models of speech quality estimation in real-time using artificial neural networks (ANNs). Speech quality is estimated in terms of MOS.

Hoene et al. [Hoene et al., 2004, Hoene et al., 2005] have employed a look-up table based approach for the derivation of their quality model. In their scheme, the quality estimates can also be used to dynamically adapt the playout time and codec's bit-rate to enhance perceived speech quality.

Conway [Conway, 2002, Conway, 2004] proposed an algorithm for estimating perceptual quality of framed speech signals using the PESQ algorithm. In this scheme the packet/frame loss pattern for a received packet/frame stream is computed. Locally, a clean speech signal is also maintained. The computed loss pattern is applied to a copy of the locally stored speech signal. As a result a distorted speech signal is formed with frame losses exactly in those locations as would be in the actual speech stream delivered to the listener of the telephone call. The distorted speech signal is compared with its clean version using the PESQ algorithm. The obtained result reflects upon the users' satisfaction of the call. A fundamental problem with this approach is that it employs the PESQ algorithm whenever speech quality has to be assessed, Whereas PESQ algorithm is both non real-time and compute intensive.

3.3.2.2 Signal-Based Methods

Signal-based non-intrusive models are preferable to parametric ones for various reasons. Firstly, parametric models can be used only with certain types of networks, such as VoIP. Secondly, signal-based models are more general in the sense that they are applicable for a wider range of distortion conditions. Unlike the parametric models, these models process the audio stream to extract the information relevant to distortions in a signal. The estimated distortions are then converted into MOS-LQO for that audio stream. Given this, a signal-based model may have two main modules. 1) A feature extractor that processes the speech signal and extracts cogent distortion indicators. 2) A mapping module that transforms the extracted features into MOS estimates. The mapping part, also referred to as the cognitive part of the system, may be derived by employing a suitable regression algorithm or a machine learning technique. Signal-based methods are also referred to as *black box* methods as, either no knowledge of the system under test is required or it is not available [Rix et al., 2006].

Liang and Kubichek [Liang and Kubichek, 1994] proposed the first signal-based model for speech quality estimation. In their work they used the perceptual linear prediction (PLP) coefficients [Hermansky, 1990] extracted from undistorted speech signals. The PLP algorithm emulates the auditory processing of the human ear. These coefficients were used to train a code-book of reference centroids. PLP coefficients of speech frames of a distorted speech signal were used to compute the Euclidean distance from their nearest reference centroids. The time-averaged Euclidean distance over the entire length of the speech signal was used as an indication of speech quality degradation. This approach has been followed in numerous subsequent research studies. The model performance was assessed by using various distortion measures used in vector quantization [Jin and Kubichek, 1995, Jin and Kubichek, 1996]. In [Picovici and Mahdi, 2004] Picovici and Mahdi proposed to form a reference code-book of PLP coefficients of clean speech signals using the *self organizing map* [Kohonen, 1990]. In [Li and Kubichek, 2003] Li and Kubichek proposed a scheme based on a hidden Markov model [Rabiner, 1989] to capture the temporal dependency between segments of human speech. Recently Falk et al. [Falk and Chan, 2006] proposed a model in which Gaussian mixture models [Everitt and Hand, 1981, Bishop, 1995] were trained separately for PLP coefficients of clean and distorted speech signals. These models were used for computing consistency measures of the speech signal under test with respect to clean and distorted reference mixture models. The consistency values were mapped to MOS obtained by subjective tests using multivariate adaptive regressive splines [Friedman, 1991].

In [Kim, 2004, Kim, 2005] Kim proposed an auditory model for non-intrusive speech quality estimation (ANIQUE). The proposed model was based on temporal envelope representation of the speech signal under test.

As opposed to modeling the human auditory system, Gray et al. proposed a model based on human vocal production system [Gray et al., 2000]. It is based on

the premise that most distortions caused by the telecommunications systems cannot be produced by human vocal production systems due to the limited motor mechanism of the human vocal tract. Thus, the derived model was sensitive to the distortions occurring in telecommunications networks.

3.3.3 ITU-T P.563

From 2002 to 2004 ITU-T held a competition to standardize a model for non-intrusive speech quality estimation. Two models were submitted namely; ANIQUE and *single-ended assessment model (SEAM)*. The former was narrowly beaten by the latter. SEAM was based on three different models including the one proposed by Gray et al. [Gray et al., 2000]. This was standardized as ITU-T P.563 [ITU-T, 2005d]. The average correlation of MOS-LQO produced by ITU-T P.563 with MOS-LQS was 0.88 over the set of 24 subjective tests used for training and testing. The overall structure of the P.563 algorithm is shown in Figure 3.4. It may be divided into three stages, namely, preprocessing, feature, extraction and perceptual mapping. Each of these is discussed below briefly.

1) Preprocessing: In this stage the signal is level normalized to -26 dBov[2]. After this, two additional versions of the distorted signal are created. The first is created by a filter having a frequency response similar to the modified intermediate reference system (IRS) as described in ITU-T P.830 [ITU-T, 1996d]. IRS emulates the frequency response of a standard telephony handset. The second version of the normalized signal is created by using a fourth-order Butterworth high-pass filter with a 100-Hz cutoff frequency and a flat response for higher frequencies, thus emulating the frequency response of cordless and mobile phones. Voice Activity Detection (VAD) is also a part of the preprocessing stage that is used to discard speech sections shorter

[2]Decibels relative to the overload point of a digital system

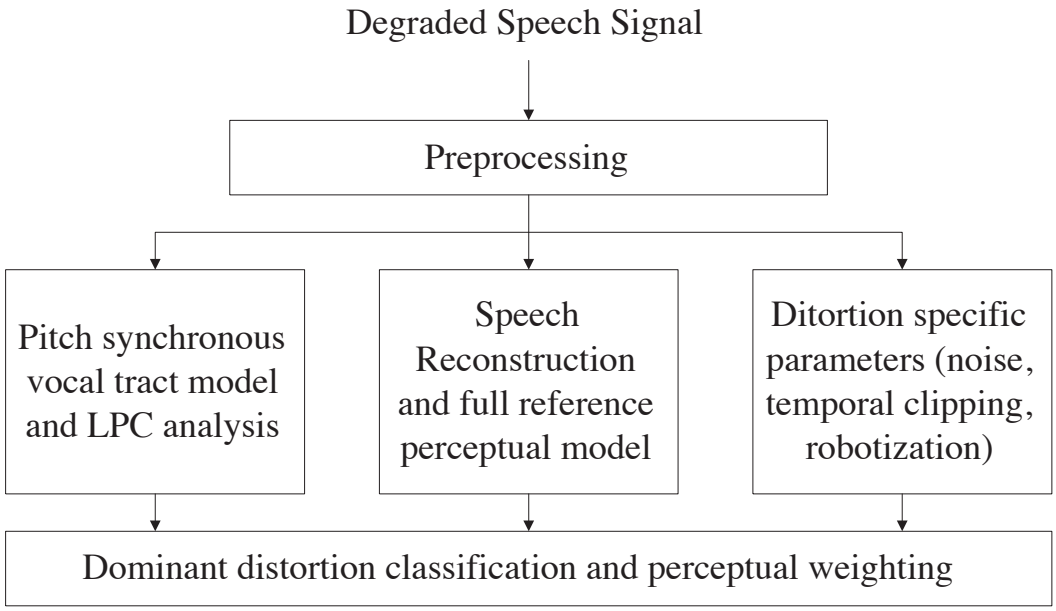


Figure 3.4: The structure of ITU-T P.563, adapted from [Rix et al., 2006]

than 12 ms and to join speech sections separated by less than 200 ms.

2) Feature extraction: This stage pertains to feature extraction which is applied on the preprocessed versions of the signal. Feature extraction is based on three basic principles. The first principle models the human vocal tract as a series of concatenated tubes to reveal the anomalies in the speech signal as a function of abnormal variations in the tubes' sections. The statistics relevant to these anomalies form the speech features.

The human vocal production system may be considered to have three components: lungs as a source of air pressure, vocal chords as source of modulation and the vocal tract as a resonating source. Thus, for *voiced* sounds, the air pressure created by the lungs excites the vocal chords to create a low frequency, quasi periodic sound. The spectral content of this sound is changed due to resonating characteristics of the vocal tract. While speaking, the shape of the vocal tract is changed due to controlled

contractions and relaxations of its muscles. This changes the resonant frequencies of the vocal tract, and consequently the spectral content of the speech. To this end, Gray et al. attempted to capture the speech distortions, caused by communications networks, by employing a human vocal production model [Gray et al., 2000]. The vocal tract is modeled as a set of concatenated tubes with uniform, time-varying cross-sectional areas. Here, it is assumed that most types of speech distortions cannot be produced by a human vocal tract due to the limited and restrained movement of the vocal tract muscles. In general terms, an implausible change in any of the tubes' sizes is considered as a distortion.

The second principle entails a reconstruction of a *pseudo* reference signal from the signal under test to perform an intrusive quality evaluation of the speech signal to estimate distortions. Signal reconstruction is done by performing a 10^{th} order *linear predictive (LP)* analysis of 5 ms frames of the distorted signal. LP coefficients are converted to *line spectral frequencies* followed by quantization to constrain them to fit the vocal tract model of a typical human talker. LP is a popular speech analysis technique used to represent characteristics of speech with a reduced set of parameters [Gold and Morgan, 1999][pp280-291]. These quantized coefficients are used to reconstruct the pseudo reference signal. The difference between the pseudo reference signal, in a spectral sense, and the signal under test gives a basic quality estimate that is used as a feature for overall quality estimation.

The third principle is to features related to specific distortions encountered in voice channels, such as temporal clipping, frame erasures, signal correlated and background noise, robotization and speech level variation.

Perceptual mapping: According to the reference implementation of the algorithm, a total of 43 features are extracted that depict various characteristics of the speech signal under test. Based on a restricted set of *key parameters*, an assignment to a dominant distortion class is made. A complete description of these features is

skipped here for brevity, but they can be divided into three distortion groups pertaining to: 1) Unnaturalness of speech, 2) noise, and 3) interruptions, mutes and temporal clipping. ITU-T P.563 uses a two step mapping process. First, an initial quality estimate is made that is a linear combination of the values of a subset of speech features that fall under a particular dominant distortion class. Second, a final quality estimate is made that is again a linear combination of the initial quality estimate and 11 additional features. P.563 has shown a high correlation with the human evaluation of speech quality, ranging between 0.88–0.90 [ITU-T, 2005d] for various ITU-T benchmark tests.

3.4 Conclusions

Various methods for speech quality estimation have been described in this chapter. It has been discussed that subjective methods are the most reliable for obtaining speech quality estimates. However, subjective methods are expensive and time consuming to conduct. In order to circumvent these issues objective speech quality estimation has become an active research area. The prediction accuracy of objective methods is generally inferior to subjective methods. However, they are cost effective and computationally efficient. The tests can also be repeated easily. The non-intrusive assessment methods, as opposed to the intrusive methods, may also be used for continuous and on-line monitoring of speech quality.

Chapter 4

Genetic Programming

4.1 Introduction

Genetic Programming (GP) [Koza, 1992] [Mitchell, 1997] is a biologically-inspired machine learning technique. It seeks to generate plausible approximate solutions to complex optimization problems by using concepts adopted, loosely, from natural evolution. It has the advantage that, unlike many other optimization techniques, it can generate solutions (or quasi-solutions) to problems in symbolic form. Although the solution representation is problem specific, it is common to use mathematical expressions or a subset of C/C++ for this purpose. GP produces human comprehensible results; an advantage when compared to approaches like Artificial Neural Networks (ANNs) where making sense out of a trained network can be quite a challenge [Mitchell, 1997, pp-85]. Another crucial advantage is that GP is not merely restricted to tuning the parameters of a pre-defined mathematical model like ANNs and other numerical optimization techniques. Instead, as in this thesis, it also discovers the model itself with the primary aim of optimizing a user defined error metric. GP does not render numerical methods totally redundant, however. It has been used

to advantage in conjunction with numerical optimization techniques such as linear regression [Keijzer, 2004], gradient descent [Topchy and Punch, 2001] and quasi-Newton [Mugambi et al., 2004]. It has been suggested that the hybrid GP/numerical methods yield superior results by allowing GP to focus at the truly innovative aspect of the work, i.e., discovery of the model structure [Keijzer, 2004].

GP is coarsely modelled on natural evolution. Biological organisms aim to overcome environmental obstacles and compete for resources in a bid for survival and reproduction. GP evolves digital populations in a similar way. The environmental challenges are defined by an error metric that each member of the population, an *individual* or a candidate solution, seeks to minimise.

4.2 Execution Steps of Genetic Programming

Initially, the population is created by randomly generating a set of candidate solutions. To allow this, the syntactic constituents of an individual are pre-specified in the form of two sets: *functions* and *terminals*. Functions are exemplified by arithmetic operators, trigonometric functions and boolean functions as they require operands to produce an output. Terminals require no arguments. They may be, *inter alia*, numeric constants, system variables and functions with constant inputs. An initial population is generated by randomly picking from these sets, although other methods exist [Banzhaf et al., 1998].

Each individual is tested on the given problem to assign it a measure of quality which is called its *fitness*. The fitness of a GP individual determines the chances of an individual surviving to the next *generation* or producing offspring. The offspring result from introducing some variation into the *selected* parent(s). Normally, there are two kinds of variation (or genetic) operators, *crossover* and *mutation*. Crossover involves combining the genetic material of different (normally two) individuals to

produce new solutions. Sometimes completely new genetic material is introduced into the offspring, albeit with a small probability. This phenomenon is called mutation, and it is observed to be useful in GP by helping the system to work its way out of local minima (which are undesired, but inevitable, artifacts of the objective function).

Clearly, the genetic operators of crossover and mutation must work in a manner so that the resulting offspring obey the syntactic constraints of the language used to represent the solutions. To facilitate this, the GP-individuals are maintained with data structures that are amenable to the carefully designed genetic operators. Abstract syntax trees are by far the most popular choice, although linear structures are also becoming common [Banzhaf et al., 1998] [O'Neill and Ryan, 2001]. Figure 4.1 shows two example GP individuals undergoing crossover and the resulting offspring. Note that the crossover point is selected randomly in each individual and the subtrees rooted at those points are exchanged during the process. During mutation, a new subtree may be randomly generated at the selected point, subject to a user specified *maximum depth* limit. This is termed *subtree mutation*. Another type of mutation is *point mutation*. In this type of mutation a point is randomly chosen in a given individual and it is replaced by a new, randomly generated node. Figure 4.2 shows examples of point and subtree mutation. As a result of the genetic operations the resulting offspring can be different in size and shape from their parents as is the case in the present example. This allows GP to explore a variable length solution space. However, to stop the trees growing arbitrarily large, again a maximum depth limit is employed. If the resulting offspring have larger depths, they are discarded. As stated earlier, the resulting offspring should respect the syntactic constraints of the underlying language. This implies, for instance, that in performing point mutation, the randomly generated node should have the same *arity* as the node to be replaced. Similarly, the subtrees chosen for crossover should have similar return data-types for error-free execution of the resulting offspring.

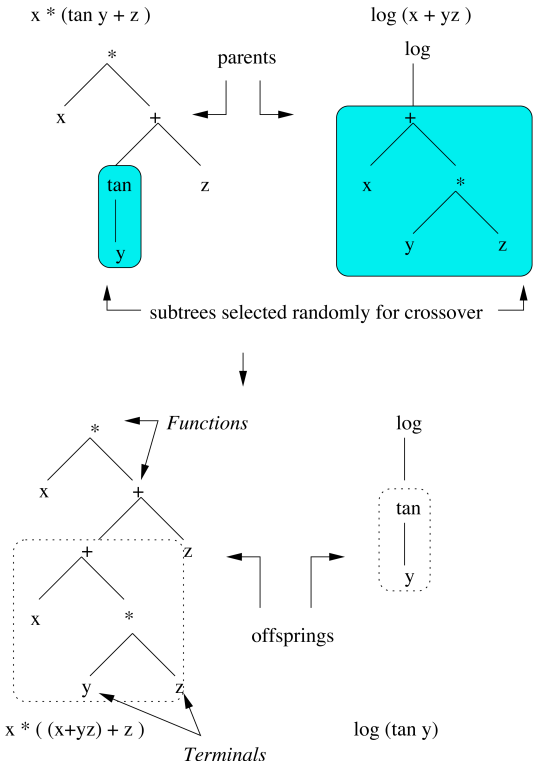


Figure 4.1: Depicted are the example abstract syntax trees for GP individuals and the corresponding expressions. Functions are the internal nodes, while the terminals appear only as the leaves. The shaded portions in the upper trees represent the subtrees to be exchanged during crossover. The resulting offspring are shown underneath with dotted boundaries marking the exchanged fragments.

With this background the overall GP algorithm can be briefly discussed now. The purpose is to breed better and better individuals as the evolution progresses through several generations until some user specified criterion is met. It may be that some success criterion is fulfilled e.g. an individual with a desired fitness value has been found or a maximum number of generations (a GP system parameter) have elapsed. Each generation typically involves the following steps (although variations exist):

1. if it is the first generation, an initialisation procedure is invoked [Banzhaf et al., 1998, pp118-122] to produce the initial population of a fixed size;

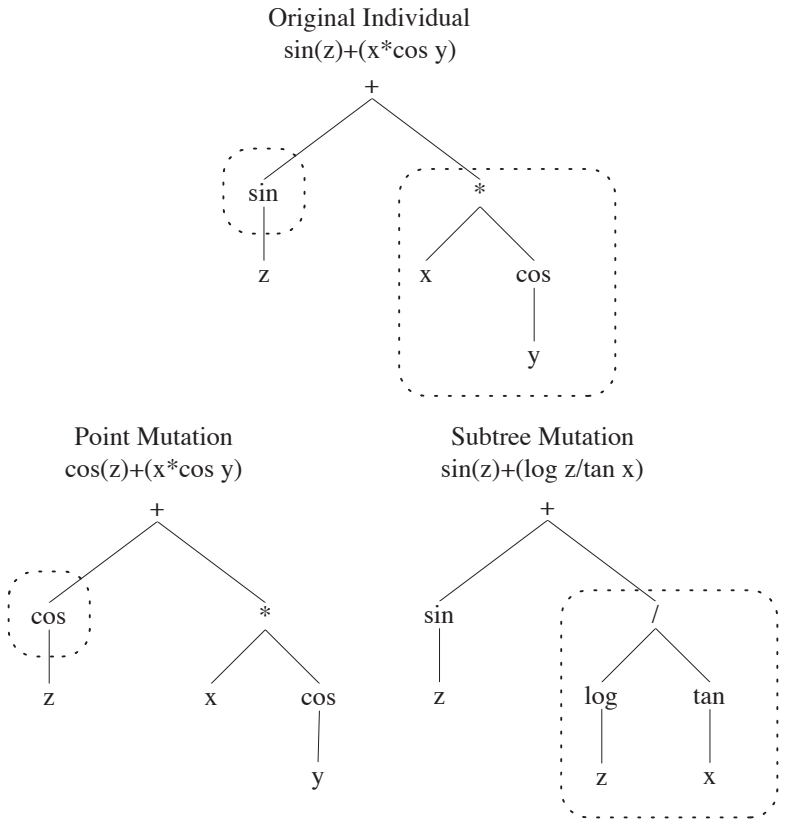


Figure 4.2: Examples of point mutation and subtree mutation are presented. The encompassed regions of the original tree have been chosen for point and subtree mutation (from left to right respectively). The resulting individuals and corresponding expressions are shown at the bottom.

2. choose two parents through a process termed *selection*. Different selection schemes exist e.g. roulette wheel selection or tournament selection. Roulette wheel selection is also termed *fitness proportionate selection* whereby an individual's chance of being selected as a parent is proportional to its fitness. In tournament selection n individuals are picked randomly from the population and the best of them is the winner. Tournament selection has proven to be a better strategy than roulette wheel selection, as it is reflected by various research

studies [Goldberg and Deb, 1990, Zhong et al., 2005];

3. crossover is applied to yield two offspring which are then subjected to mutation. Typically crossover is used with a high probability (e.g. 90%) while mutation is used sparingly (1%);

4. evaluate the fitness of the two offspring;

5. if the number of offspring generated so far have reached a user specified limit, follow on to the next step. Otherwise, go to step 2;

6. in this study, the offspring and parent populations are considered together to keep the best performers for the next generation. The rest of the individuals from either pool are discarded. Other schemes may keep all the offspring as the population members for the next generation.

A number of generational cycles constitutes a GP *run*. Due to the stochastic nature of the evolutionary process, each run of GP can produce individuals that are different from those of other runs despite the same system parameters and fitness criteria. Therefore, it is a regular practice to conduct several runs in order to have different results of competitive quality and also to have a statistical justification of the behavior of GP. Detailed accounts of various aspects of GP can be found in [Koza, 1992] [Banzhaf et al., 1998].

4.3 Numerical Parameter Tuning in GP

The essential merit of GP is its ability to find a viable *structure* of the target model. In this, it differs from traditional optimization algorithms which aim at tuning the parameters of an *already specified* model. Parameter tuning is also implicitly inherent in GP's search mechanism and may be accomplished in two different ways. Firstly,

Koza has described this in [Koza, 1992], where he argues that GP can combine terminals in an innovative fashion to find suitable coefficients for evolving models. An example is used to describe how (x/x) produces a constant value of 1, and eventually applying the *sin* function to it produces a value of 0.841471.

However, this requires the application of possibly a large number of carefully conducted crossover and/or mutation operations before the desired constant is found and attached to an appropriate node of a GP in order to lend the desired effect. This process may span a considerable number of generations and may in turn become computationally inefficient.

Secondly, when running a GP experiment that is expected to yield a final individual with a few constants in it, it is common practice to attach the real number(s) $\Re$, known as the ephemeral random constant, as terminal(s) to the individuals of the first generation. This number is chosen probabilistically and, whenever it is chosen, it is replaced with a randomly generated real number. Given that this number is chosen probabilistically, an individual may have none or multiple random numbers attached to it. These numbers either themselves, or in combination with other terminals and/or functions, by forming more useful ones as mentioned above, serve as the constant coefficients of the models being evolved. In fact, Koza noted in [Koza, 1992] that very few of the initial constants appear unmodified in the final generation. In other words, in most of the cases constants are combined with other terminals and functions to form new ones. This is tantamount to the same problem stated above i.e. evolution requires larger number of generations and leads to computational inefficiency.

4.3.1 Hybrid Optimisation in GP

A few approaches have considered the problem of efficiently attaching constants to GP individuals. In [Keith and Martin, 1994] Keith and Martin employed a *prefix*

jumptable. In this approach, in order to accommodate constants a separate array of floating point values is maintained. The genome simply consists of a linear array of indices. In the case where a gene represents a constant, it points to an entry in the array of floating point numbers. However, since the array is of a small size only a small and finite set of constants can be used.

Additionally, various meta-heuristic and numerical parameter optimization methods have been used in conjunction with GP to create hybrid schemes for optimization. In [Howard and D'Angelo, 1995] Howard and D' Angelo proposed a hybrid GA-P algorithm, where a genetic algorithm (GA) was used in conjunction with GP. Here GP would evolve the structure of the individual programs and the constants of each individual would be tuned with a GA. To achieve this, constants in a tree are indices into an array of values. However, here each individual has its own array of values on which search can be performed.

In [Sharman et al., 1995] Sharman et al. introduced a hybrid scheme by applying simulated annealing to GP trees to evolve signal processing algorithms for a problem concerning channel equalization. Here the mechanism of tuning constants is slightly different from that used in GA-P hybrid. In GA-P the constants are inherent parts of the GP trees. Here the constants are associated as *node gains* to the edges between nodes of a given GP tree. The methodology of appending node gains to edges is somewhat analogous to assigning weights to nodes in artificial neural networks [Mitchell, 1997]. The node gains associated with all the edges are maintained in a separate array for each tree. The search is applied on this array for each tree. The simulated annealing algorithm may be briefly described as follows:

Let $\alpha_{pq}(i)$ be the node gain associated with edge pq at iteration i.

1. Perturb $\alpha_{pq}(i)$ to get $\alpha'_{pq}(i)$ for all pq

2. Evaluate the fitness $f'(i)$ using these perturbed parameters.

3. If $(f'(i) > f(i))$, then accept the perturbed node gains and continue.

4. Else, accept the perturbed node gains with *some* probability that is a function of annealing *temperature (T)* and continue.

5. Reduce the annealing temperature (T) according to some *cooling rate* and go to step 1. Stop if some user specified criteria is met.

The notions of annealing temperature and cooling rate are of central importance to simulated annealing. During initial iterations the annealing temperature is kept high. This allows the algorithm to accept perturbations that yield poor fitness with a higher probability. This in turn allows the algorithm to, possibly, escape the trajectories that lead to locally optimum solutions. As the simulation proceeds, the annealing temperature is reduced at a certain cooling rate so as to adopt a more conservative approach towards accepting *bad* perturbations. This allows the algorithm to converge to some optimum solution in the vicinity [Kirkpatrick et al., 1983].

In [Esparcia-Alcázar and Sharman, 1997] Esparcia-Alcázar and Sharman further expand and elaborate on their suggested methodology. They performed four evolutionary experiments. In the first three they initialize node gains at random while creating the initial population. In the fourth they do not use node gains while evolving models. In one of the first three experiments they induce Darwinian evolution while adapting node gains with simulated annealing. Darwinian evolution implies that the node gains learnt by an individual during its lifetime (i.e. learnt by simulated annealing after its creation through crossover and mutation) are not carried over to its offspring. In another experiment Lamarckian evolution was emulated. Lamarckian is another classical theory of evolution. It suggests that the behavior learnt by an organism during its lifetime may be incorporated in to its genetic makeup, and eventually may transmit to the offspring. In this experiment the node gains learnt by simulated annealing are carried over to the offspring of that individual. Finally, in

the third experiment the node gains undergo some random mutations and are carried over to the offspring. Based on the results obtained for various problems they conclude that evolution along with parameter optimization (with simulated annealing) performs better than with GP alone.

In [Topchy and Punch, 2001] Topchy and Punch performed non-linear optimization using the gradient descent algorithm for the local search of leaf coefficients of GP trees. Moreover, the quasi-Newton method has been used to achieve the same objective in [Mugambi et al., 2004].

There is a general consensus among researchers that for various problems hybrid GP approaches perform better than GP alone. However, there are a number of issues associated with using a parameter optimization algorithm along with GP to find appropriate constants. The most predominant of these are the additional computational requirements and the lack of knowledge of the particular problem domain.

Cogent questions which may arise while embarking on the implementation of a hybrid optimization approach are: that how many coefficients should the expected model have, or what should be the range of those coefficients? The answers to these are usually not known for numerous problem domains and all an experimenter can do is to rely on heuristics and guesswork. Similar questions as regards the configuration of the optimization algorithm also need to be addressed. These include, for instance, in the case where a GA is being used, questions regarding the population size, operator probabilities, and number of generations. In simulated annealing these could be number of iterations of the algorithm, annealing temperature and cooling rate. In numerical optimization algorithms also, questions regarding the number of iterations and learning rate are important. Clearly, some of these variables are clearly linked to the nature of the underlying model and the number of coefficients. However, due to the varying nature of models at any given time in a GP population, these questions cannot be addressed fairly. Normally the only choice the experimenter has is to rely

on empirical studies. The choice of these parameters also affects the performance of the GP system. Thus, it becomes important to decide whether to tune the coefficients of all models being evolved by GP or to choose a subset of them.

4.3.2 Scaled Symbolic Regression

Normally the objective in GP based symbolic regression is to reduce the *mean squared error (MSE)* between the instances of the *target* data of a particular problem domain and the corresponding output values produced by the individuals of a GP system. An individual that has a small MSE against the target data is considered as a better candidate solution. MSE is given by equation (4.3.1)

$$MSE(y,t) = 1/n \sum_{i}^{n} (t_i - y_i))^2 \tag{4.3.1}$$

where y is a GP evolved function of the input parameters in this case (a mathematical expression), y_i represents the output value produced by y for the input case i and t_i represents the corresponding target value.

In [Keijzer, 2003, Keijzer, 2004] Maarten Keijzer proposed a technique to reduce the *scaled* mean squared error (MSE_s) instead,

$$MSE_s(y,t) = 1/n \sum_{i}^{n} (t_i - (a + by_i))^2 \tag{4.3.2}$$

where a and b adjust the slope and y-intercept of the evolved expression to minimise the squared error. They are computed as follows:

$$a = \overline{t} - b\overline{y}, b = \frac{cov(t,y)}{var(y)} \tag{4.3.3}$$

In effect this scheme linearly regresses a given model to the target data during evolution. This scheme has some special properties. Firstly, it is expected to perform better than the simple MSE measure for most of the problems in symbolic regression. Rather, it has been proven by Keijzer in [Keijzer, 2004] that $MSE_s \leq MSE$ for

any arbitrary problem concerning symbolic regression. The introduction of the slope and intercept term make it easier for the GP to learn constant terms through linear regression, which would otherwise be difficult to search.

Another crucial advantage of this scheme is that it is computationally cheaper than most of the other hybrid approaches. The operations defined by equation (4.3.3) can be performed in O(N) time [Keijzer, 2003].

4.4 Advantages of GP

GP searches for a plausible solution from the space of *computer programs*. The search process begins with a set of randomly generated programs in the search space. These programs correspond to *points* in the GP search space. The programs with possibly better quality are used to generate new programs corresponding to new points in the search space using genetic operators such as crossover, mutation, reproduction etc. The process is repeated iteratively until an individual program is found that meets the desired performance criterion.

The great benefit of GP lies with its ability to search for the appropriate structure of a target solution. To this end, GP is distinguishable from traditional optimization approaches. It has already been mentioned in section 4.3 that some capability for finding appropriate constants for the target model is inherent in GP. Such a capability can also be enforced by hybridizing GP with an appropriate parameter optimization algorithm. Altogether GP is a useful tool for learning models of an arbitrary intricacy. This may include linear as well as nonlinear models. GP also has an additional advantage of pruning off the redundant system information during evolution. Since GP's evolutionary process follows the *'survival of the fittest'* paradigm, it is likely to weed out individuals having redundant system variables as genomes. To the contrary, only individuals that depend on the salient system variables potentially survive to the

end of a run. This can be useful in finding concise models that depend on the relevant data. To this end, GP also has the ability to perform a principal components analysis of a particular problem domain. Lastly, given that GP embodies a stochastic search technique, it has the ability to find a *globally optimum* model for a given problem domain.

4.5 GP environment

For most of the work GPLab was used as the preferred GP environment. GPLab[1] is a Matlab toolbox for GP developed by Sara Silva. As compared with the GP environments built in other programming evironments it has the benefits of being easily configurable and easy to program. However, it is computationally much slower than contemporary systems written in laguages such as C or Java.

For some experiments, concerning the development of a signal-based model, a new GP environment was developed in Java. Its software design was inspired from Beagle Puppy[2] software [Gagné and Parizeau, 2006]. Beagle Puppy is a GP environment written in C. Some features were inherited from GPLab and research literature on other useful techniques. A capability of hybrid optimization was also introduced by implementing and integrating a GA to it. The modular design of this system allows for easy integration of any of the other parameter optimization techniques with it. Salient features of this system are described in more detail in section 7.3.1.

[1] http://gplab.sourceforge.net/
[2] http://beagle.gel.ulaval.ca/puppy/

Chapter 5

Real-Time, Non-Intrusive Evaluation of VoIP

5.1 Introduction

In this chapter we employ a Genetic Programming (GP) based symbolic regression approach to estimate VoIP speech quality as a function of impairments due to IP network and encoding algorithms. It was suggested earlier (in chapter 4) that the main advantage of GP is that it can produce human-readable results in the form of analytical expressions. Moreover, GP deals with the significant input parameters and aids in the automatic pruning of irrelevant ones. These features of GP make our results superior to the past research based on Artificial Neural Networks (ANNs) by Sun and Ifeachor [Sun and Ifeachor, 2002a], Mohamed et. al. [Mohamed et al., 2001] [Mohamed et al., 2004] and on lookup tables by Hoene et. al. [Hoene et al., 2004]. We have employed a number of modern narrowband (NB) codecs to derive speech quality estimation models. We have also used the NB version of PESQ as a reference for evolutionary modeling. The results of proposed models show a high correlation with PESQ. Moreover, our models are suitable for real-time and non-intrusive estimation of VoIP quality.

The rest of the chapter is organized as follows: Section 5.2 describes the VoIP

experiment environment to gather the relevant data characterizing the speech traffic. Section 5.3 elucidates how this data is used to evolve the speech quality estimation models. Section 5.4 presents the results and carries out an analysis of the current research. Section 5.5 performs a descriptive comparison of the research presented in this chapter with existing approaches. The chapter concludes in section 5.6 outlining the major achievements and future ambitions.

5.2 VoIP Traffic Simulation

A simulation based approach was pursued for this research. Such an approach has been employed by various authors such as [Pennock, 2002] [Sun and Ifeachor, 2002b]. The main advantage of this approach is that various network distortion scenarios can be emulated precisely. Moreover, the tests are easily repeatable. This section describes the VoIP experiment methodology employed in this work.

A schematic of the simulation environment is shown in Figure 5.1. The system includes a speech database, encoder(s)/decoder(s), a packet loss simulator, a speech quality estimation module (PESQ), a parameter extraction module for computing the values of different parameters and a GP based speech quality estimation model. A VoIP packet may either have talkspurt frames or silence frames included in it.

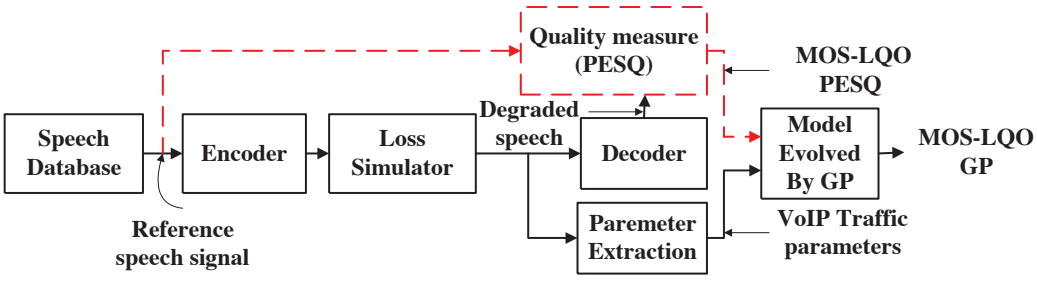


Figure 5.1: Simulation System for Speech Quality Estimation Model

These frames can be distinguished if Voice Activity Detection (VAD) is enabled at

the encoder. In this case a silence frame is represented by an SID (Silence Insertion Description) frame. In the rest of the Chapter any network parameters subscripted with VAD correspond to talkspurt frames only. Unsubscripted parameters correspond to real network traffic. For instance, any use of the term mlr_{VAD} refers to mean loss rate of talkspurt frames only. The term mlr, however, refers to the mean loss rate of the overall network traffic of a particular VoIP call.

Three popular NB codecs were chosen in the current research, namely; G.729 CS-ACELP (8 kbps) [ITU-T, 1996a], AMR-NB [ETSI, 2000] and G.723.1 MP-MLQ/ACELP (6.3/5.3 kbps) [ITU-T, 1996b]. All of these are based on Linear Predictive Coding (LPC) of speech. LPC is a scheme whereby the spectral envelop of human speech can be represented in a compressed form. AMR was used in its 7.4 and 12.2 kbps modes whereas G.723.1 was used in its 6.3 kbps mode only. All of these low bit-rate codecs aim at VoIP traffic bandwidth saving. These codecs also have built-in VAD and PLC mechanisms.

The choice of network simulation characteristics was driven by ITU-T Recommendation G.1050 [ITU-T, 2005c] which describes a model for evaluating multimedia transmission performance over an IP network. Bursty packet loss was simulated using the 2-state Markov model described in section 2.4.1.1 (Figure 2.3). It also models packets discarded by the playout buffer due to late arrivals. Packet loss was simulated for different values of *mlr* and *conditional loss probability (clp)*. Twelve different values for *mlr* were chosen; 0, 2.5, 5, 7.5, 10, 12.5, 15, 20, 25, 30, 35 and 40%. The peak loss-rate (i.e. 40%) was kept an order of magnitude higher than that specified for an unmanaged network in ITU-T G.1050 (i.e. 20%) so as to gather more representative data for model derivation. For each value of *mlr*, *clp* was set to 10, 50, 60, 70, and 80%.

After subjecting the VoIP streams under test to various network impairments, they were evaluated using NB version of the PESQ algorithm. The PESQ algorithm

compares a degraded speech signal with a reference (clean) speech signal and computes an objective MOS score ranging between -0.5 and 4.5, albeit for most cases the output will be between 1.0 and 4.5. It must be mentioned that PESQ simulates a listening test and is optimized to represent the average evaluation (MOS) of all listeners. It is statistically proven that the best possible result that can be obtained from a listening only test is never 5.0, hence it was set to 4.5 [ITU-T, 2001b]. The PESQ algorithm is widely acclaimed for its high correlation with the results of formal subjective tests for a wide range of network distortion conditions. It is the current *de jure* standard for objective speech evaluation specified by ITU-T. In the current context, the MOS scores obtained by the PESQ algorithm and the MOS predicted by the GP based model are differentiated by the abbreviations $MOS\text{-}LQO_{PESQ}$ and $MOS\text{-}LQO_{GP}$ respectively. The term *MOS-LQO* is an acronym for *Mean Opinion Score-Listening Quality Objective* and the various subscripts are used to identify the objective quality estimation models used. This terminology is based on [ITU-T, 2003b].

Altogether, five VoIP traffic parameters have been chosen in the current analysis which form the input variables for evolutionary modeling. These parameters are: codec bit-rate (kbps), packetization interval (ms) (abbreviated as PI), frame duration (ms), mlr_{VAD} and mbl_{VAD} (mean burst length of talkspurt frames) . A lower value of bit-rate corresponds to a higher compression of the speech signal, thus resulting in a lower bandwidth requirement at the expense of quality. The packetization interval, which is the payload size of a VoIP packet, was varied between 10 to 60 ms. Considerable bandwidth saving can be achieved by encapsulating multiple speech frames in one VoIP packet thus reducing the need for RTP/UDP/IP headers that would have been required for encapsulation and transportation of speech frames if they were to be sent individually. However, higher packetization intervals have certain associated drawbacks too. First, the end-to-end delay of the VoIP stream is increased as the

sender has to buffer speech frames for a considerable duration before subsequent frames become available by the encoder. Second, for a large packetization interval, typically higher than 40 ms, loss of a single packet results in noticeable degradation of speech quality. Hence, packetization interval presents a trade-off between the speech quality and bandwidth saving. Frame duration has a similar effect on the quality as that of packetization interval. Higher frame durations may have other disadvantages, for instance, in LPC a speech signal is assumed to be stationary (non-transient) for a given frame duration. However, for higher frame durations this assumption may considerably deviate from the reality. Thus, a codec with such a feature may distort the final speech content. The parameter extraction module (Figure 5.1) is used to obtain the values of the aforementioned parameters from the VoIP traffic stream under test. The corresponding $MOS\text{-}LQO_{PESQ}$ of the decoded VoIP stream under test subjected to these network conditions forms the target output value for training purposes. In actual VoIP applications this information would be gathered by parsing the RTP headers and bitstreams of the encoded frames. The information would then be used as an input for the GP based model to estimate $MOS\text{-}LQO_{GP}$ after processing.

5.3 Experimental Setup

As discussed earlier GP was the machine learning algorithm of choice for deriving a mapping between network traffic parameters and VoIP quality. GPLab was used as the preferred GP environment in this study. Four GP experiments with different configurations were conducted for empirical reasons. The common parameters of all the experiments are listed in Table 5.1. In all of the experiments the population size was set to 300. Each experiment was composed of 50 runs whereas each run spanned 50 generations. Adaptive genetic operator probabilities were used [Davis, 1989]. In this scheme the operator probabilities are changed at run-time. The algorithm keeps track

of some information regarding each new offspring that is produced. This includes the operators used for its creation and identities of its parents. Moreover, information on how much better (or worse) a given offspring is when compared to the best or worst individual of the preceding generation is also included. An offspring is assigned a credit based on this information. All of this information related to offspring is fed to a repository that can hold a fixed number of entries. The entries enter and leave this repository on a *first in first out* basis. After every predefined interval, the performance of each genetic operator is computed by summing the credits of all offspring in the information repository, and dividing the sum by the number of offspring in the repository produced by the respective operator. A percentage of the current value of each operator's probability is changed by a value proportional to the value of performance of the respective operator.

Tournament selection with lexicographic parsimony pressure (LPP) [Luke and Panait, 2002] was used in all of the experiments. In this selection strategy a group of G ($G \geq 2$) individuals is picked randomly from the current population. The individual with the highest fitness in the group is selected as a parent. In the case of a tie between two or more individuals, their expression sizes are compared with the smaller individual winning out. If both fitness and size are the same then an individual is chosen at random. This strategy prefers smaller individuals and helps in reducing the tendency to produce over-complicated expressions and consequently code growth. The phenomenon of growth is also referred to as *code bloat* in GP. Survival was based on elitism. The elitist criterion was such that half of the population of a new generation would be composed of best individuals from both parents and children. The other half of the population would be formed of remaining children on the basis of fitness. This elitism criteria is termed as *half elitism* in GPLab.

In experiment 1 mean squared error (MSE) was used as the fitness function and tournament size was set to 2. For experiment 2 (and subsequent experiments) scaled

Table 5.1: Common GP Parameters among all experiments

Parameter	**Value**
Initial Population Size	300
Initial Tree Depth	6
Selection	Lexicographic Parsimony Pressure Tournament
Tournament Size	2
Genetic Operators	Crossover and Subtree Mutation
Operators Probability Type	Adaptive
Initial Operator probabilities	0.5 each
Survival	Half Elitism
Generation Gap	1
Function Set	plus, minus, multiply, divide,sin, cos, log_2, log_{10}, log_e, sqrt, power,
Terminal Set	Random real-valued numbers between 0.0 and 1.0. Integers (2-10). mlr_{VAD}, mbl_{VAD}, PI, br, fd

mean squared error (MSE_s) was used as the fitness criterion and is given by equation (5.3.1).

$$MSE_s(y,t) = 1/n \sum_{i}^{n} (t_i - (a + by_i))^2 \tag{5.3.1}$$

where y is a function of the input parameters (a mathematical expression), y_i represents the value produced by a GP individual and t_i represents the target value which is produced by the PESQ algorithm. a and b adjust the slope and y-intercept of the evolved expression to minimize the squared error. This approach is known as *linear scaling* [Keijzer, 2004] and was also discussed in section 4.3.

Experiment 1 employed *protected* versions of various functions as these are implemented in GPLab like most of the contemporary GP systems. Thus, to protect against division by zero, GPLab has a division function, *divide*, that returns a value of 0 if the denominator is equal to 0. Similarly, the *sqrt* function also returns 0 upon receiving a non-positive number as an input. As another example, the logarithmic functions return 0 upon receiving 0 as input. These protections are aimed at prohibiting these functions from returning undefined values and/or complex numbers, and to

ensure that an individual produced by symbolic regression always returns numeric values on any input. However, the use of protected individuals can lead to undesired phenomena in the output range of such an individual. Thus, even though an individual might perform effectively on the training set, it might yield erroneous results when tested on a data set that covers the input domain more densely [Keijzer, 2003].

Consequently, in experiment 2 (and subsequent experiments) protected functions were not used. Instead any inputs were admissible to all the functions. For input values outside the domain of the functions *log, sqrt, division* and *pow*, NaN (undefined) values are generated. This results in the individual concerned being assigned the worst possible fitness.

The selection criterion in experiments 3 and 4 was based on the notion that population diversity can be enhanced if mating takes place between two, fitness-wise, dissimilar individuals, as suggested by Gustafson et. al. [Gustafson et al., 2005]. This selection scheme has been shown to perform better in the symbolic regression domain and, hence, it was employed in this research. This simple addition to the selection criterion only requires one to ensure that mating does not take place between individuals of equal fitness. In experiment 4 the maximum tree depth was changed from 17 to 7 to see if parsimonious individuals with performance comparable to those of earlier experiments can be obtained. Statistics pertaining to experiments and the results are presented in the next section.

5.4 Results and Analysis

Nortel Networks speech database containing high quality voice signals was used for analysis [Thorpe and Yang, 1996]. The database contains 240 speech files corresponding to two male (m_1, m_2) and two female (f_1, f_2) speakers. Duration of speech signals in the files is between 10-12s. A total of 3,360 speech files were prepared for

various combinations of afore-mentioned values of network traffic parameters. The experiment parameters include frame duration, bit-rate, packetization interval, *mlr* and *clp*. 70% and 30% of the data of distorted speech files corresponding to speakers m_1 and f_1 were used for training and testing of the evolutionary models respectively. Distorted speech files corresponding to speakers m_2 and f_2 were used to validate the performance of the chosen model against speaker independent data. In other words, network traffic parameters and corresponding $MOS\text{-}LQO_{PESQ}$ of 1177, 503 and 1680 speech files were used for training, testing and validation respectively.

Table 5.2(a) lists the statistics about the MSE of the training/testing data and of final tree size (in terms of number of nodes) of the 4 experiments under consideration. A Mann-Whitney-Wilcoxon test was also performed to decide if a significant difference exists between the experiments. Its results are tabulated in Table 5.2(b). At 5% significance level a '0' in the tableau indicates that no significant difference exists between the two experiments with respect to that *metric* (i.e. MSE_{tr}, MSE_{te} or $Size$). A '1' indicates the converse and an 'x' marks that the metric is not to be compared with itself.

Table 5.2: Statistical analysis of the GP experiments

(a) MSE Statistics for Best Individuals of 50 Runs for experiments 1-4

	$Sim1$			$Sim2$			$Sim3$			$Sim4$		
Stats	MSE_{tr}	MSE_{te}	$Size$	MSE_{tr}	MSE_{te}	$Size$	MSE_{tr}	MSE_{te}	$Size$	MSE_{tr}	MSE_{te}	$Size$
Mean	0.0980	0.1083	42.6	0.0414	0.0430	38.8	0.0434	0.2788	28.5	0.0436	0.0436	18.0
Std. Dev.	0.0409	0.0507	24.1	0.0040	0.0044	21.2	0.0042	1.0986	15.1	0.0037	0.0060	7.1
Max.	0.2135	0.2656	103	0.0543	0.0568	104	0.0519	6.8911	74	0.0520	0.0782	38
Min.	0.0449	0.0464	8	0.0368	0.0370	5	0.0378	0.0390	9	0.0370	0.0387	8

(b) Results of Mann-Whitney-Wilcoxon Significance Test

	$Sim1$			$Sim2$			$Sim3$			$Sim4$		
Stats	MSE_{tr}	MSE_{te}	$Size$	MSE_{tr}	MSE_{te}	$Size$	MSE_{tr}	MSE_{te}	$Size$	MSE_{tr}	MSE_{te}	$Size$
Sim1	x	x	x	1	1	0	1	1	1	1	1	1
Sim2	1	1	0	x	x	x	1	0	1	1	1	1
Sim3	1	1	1	1	0	1	x	x	x	0	0	1
Sim4	1	1	1	1	1	1	0	0	1	x	x	x

A keen look at the tables 5.2(a) and 5.2(b) shows that experiment 2 (which used linear scaling) performed significantly better than experiment 1. When we compare it with experiment 3, we see that experiment 3 produces significantly smaller trees than experiment 2, albeit with marginally inferior fitness. Finally, experiment 4 exhibits similar traits, as its fitness is marginally worse again, although its trees are significantly smaller. The objective in the current research was to find fitter individuals with small sizes. Hence, experiment 4 was scavenged for plausible solutions.

Figure 5.2 delineates the significance of various network traffic parameters in terms of the number of best individuals using them in each of the four GP experiments. It turns out that mlr_{VAD} had a 100% utility in all of the experiments. Codec bit-rate (br) and frame duration (fd) were the second and third most frequently availed parameters respectively. Where as, both PI and mbl_{VAD} have shown advantage in least number of runs of all experiments.

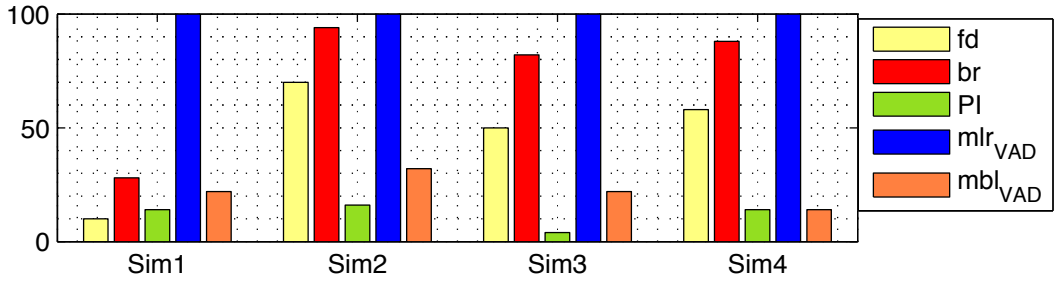


Figure 5.2: Percentage of the best individuals employing various input parameters in the 50 runs of each of the four experiments

Two of the models derived from this work are shown by equations (5.4.1) and (5.4.2). The MSE_s and Pearson's product moment correlation coefficients (σ) of equations (5.4.1) and (5.4.2) are compared with each other in Table 5.3. Equation (5.4.2) is a function of mlr_{VAD} solely. Whereas equation (5.4.1), which was the best model discovered, additionally has br and fd as independent variables. Figure 5.3

shows the scatter plots of equation (5.4.1) for training and testing data. It is noticeable that equation (5.4.2) which is a function of mlr_{VAD} only has comparable fitness to equation (5.4.1). Evaluating a single variable would be computationally cheap for a real time analysis. In the light of this and the earlier discussion on Figure 5.2 mlr_{VAD} seems to be the most crucial parameter for VoIP quality estimation.

$$MOS - LQO_{GP} = -2.46 \times log\left(cos(log(br)) + mlr_{VAD} \times (br + fd/10)\right) + 3.17 \quad (5.4.1)$$

$$MOS - LQO_{GP} = -2.99 \times cos\left(0.91 \times \sqrt{sin(mlr_{VAD})} + mlr_{VAD} + 8\right) + 4.20 \quad (5.4.2)$$

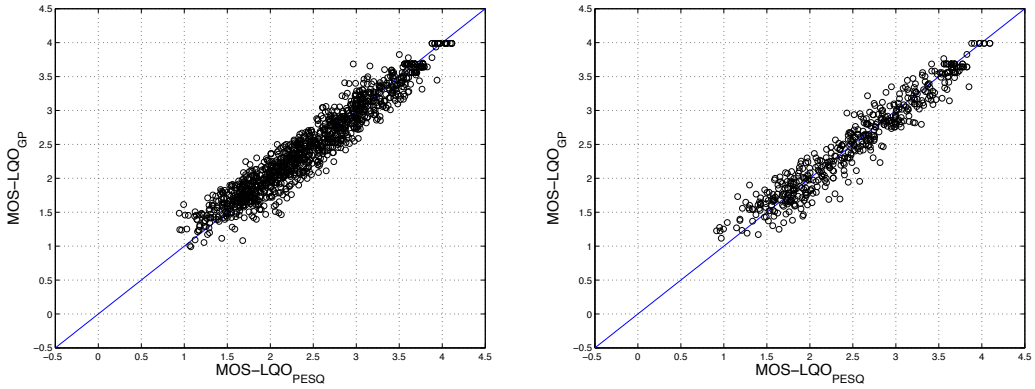
Table 5.3: Performance Statistics of the Proposed Models

	Equation (5.4.1)		**Equation(5.4.2)**	
Data	MSE_s	σ	MSE_s	σ
Training	0.0370	0.9634	0.0520	0.9481
Testing	0.0387	0.9646	0.0541	0.9501
Validation	0.0382	0.9688	0.0541	0.9531

5.4.1 On Modeling the Effect of Burstiness

It is worth mentioning that although mbl_{VAD} (a measure of burstiness) is considered to be one of the pivotal degradation sources in VoIP quality, it only appeared in 14% of the individuals generated by experiment 4. Moreover, the proposed models do not include mbl_{VAD}. It is speculated that the insignificant role of mbl_{VAD} in the overall evolutionary process is due to the ineptness of PESQ algorithm to model human perception of speech quality under bursty packet loss conditions.

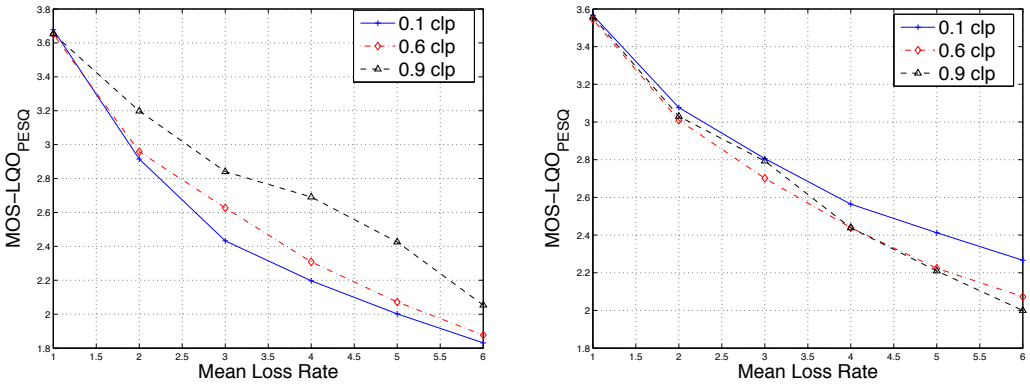
To validate this hypothesis a separate series of tests was conducted to assess the performance of PESQ for various combinations of *mlr* and *clp*. AMR and G.729 were



(a) (b)

Figure 5.3: MOS-LQO predicted by the proposed individual vs MOS-LQO measured by PESQ for (a) training data and (b) testing data for equation 5.4.1

chosen for this test and packet size was set to one frame/packet. Figure 5.4 shows the $MOS\text{-}LQO_{PESQ}$ values for speech files distorted due to various combinations of *mlr* and *clp*. Each data point in both of the figures represents the mean $MOS\text{-}LQO_{PESQ}$ of 40 speech files subjected to similar values of *mlr* and *clp*. Ideally, sharp gradients would be expected for the curves representing speech quality at higher values of *clp*; meaning that speech quality declines sharply as *clp* increases. This, however, is not the case. Rather it can be seen from Figure 5.4(a) that $MOS\text{-}LQO_{PESQ}$ is larger for higher values of value of *clp* (equal to 0.9) than for lower values. In Figure 5.4(b), however, this is not the case but the difference between $MOS\text{-}LQO_{PESQ}$ at same *mlr* but different *clp* is also not conspicuous. A visual analysis shows that PESQ does not model the widely accepted notion of burstiness on human perception of speech quality. Our conclusion about PESQ in terms of its effectiveness in bursty packet loss scenarios conforms to the results presented in [Pennock, 2002] and [Sun and Ifeachor, 2002b].



(a) (b)

Figure 5.4: $MOS\text{-}LQO_{PESQ}$ vs mlr for various clp values: (a) for AMR and(b) for G.729

5.4.2 On the Significance of Packetization Interval

Packetization interval (PI) is also not a part of the proposed models. It was most utilized in experiment 2, where only 16% of the resulting individuals were functions of PI. PI, however, is a significant input parameter. Various studies, including [Jiang and Schulzrinne, 2002], have reported that the degree of burstiness depends on PI; the larger the value of PI, the worse the effect of burstiness on speech quality. On the other hand, in [Sun and Ifeachor, 2002a] Sun and Ifeachor have reported that speech quality is not affected by PI in general. Given this, the effect of PI on speech quality was thought worthy of further investigation. G.729 was chosen as the preferred codec as it has a frame duration (fd) of 10 ms and the PI can be increased to 60 ms steps of 10 ms, as opposed to other codecs. Smaller increments of PI may be instrumental in revealing variation of speech quality as a function of PI at a better resolution. This was done by keeping the clp fixed at 0.7 and mlr was varied between 0% to 55% in incremental steps of 5% each. For each value of mlr the packetization interval was varied between 10 to 60ms. It is obvious from Figure 5.5 that, in general, packetization

interval has no obvious effect on speech quality. The speech quality decreases as the packet loss rate increases but remains, somewhat, steady across various packetization intervals.

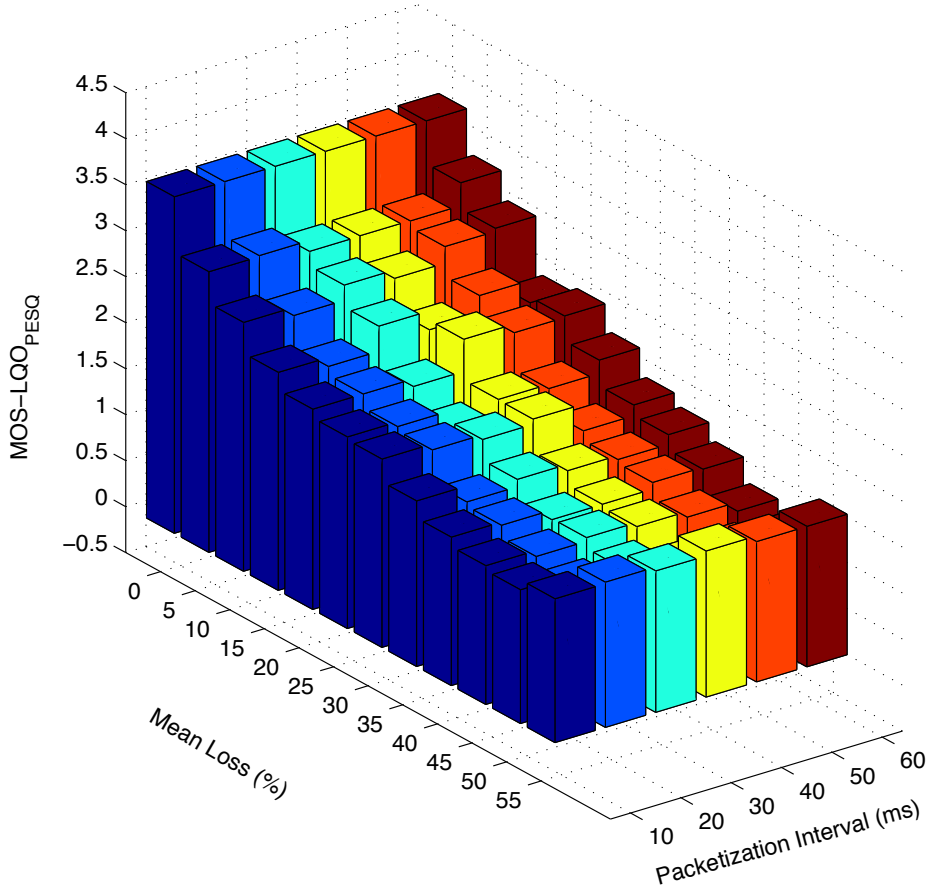
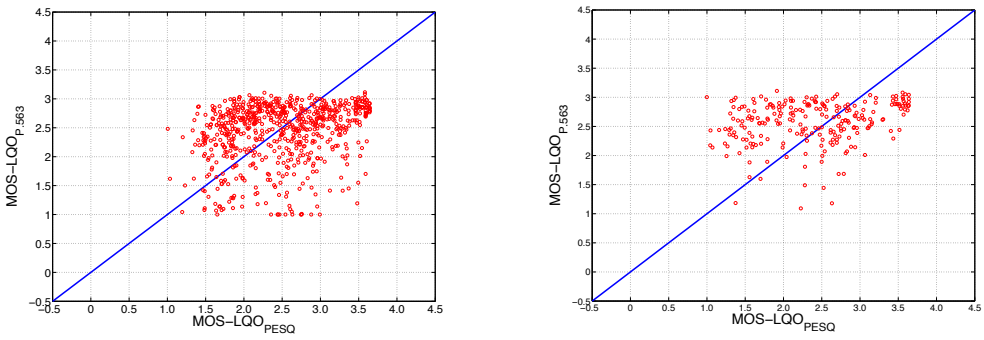


Figure 5.5: The values of $MOS\text{-}LQO_{PESQ}$ at various values of mlr and packetization intervals for G.729 codec. The clp was set to 0.7

5.4.3 On the Performance of ITU-T P.563

As stated earlier ITU-T P.563 [ITU-T, 2005d] is the new recommendation for non-intrusive speech quality estimation. A correlation analysis was done between $MOS\text{-}LQO_{PESQ}$ and the corresponding objective MOS values obtained by ITU-T P.563 ($MOS\text{-}LQO_{P.563}$). It turns out that the correlation coefficients (σ) varied between 0.65-0.82 under various network traffic conditions. This also highlights the superiority of the proposed models as they have better prediction accuracies as compared with ITU-T P.563. It is reiterated to emphasize that ITU-T P.563 is a non-real-time process as it relies upon complex *digital signal processing* techniques to estimate the quality of the speech signal under test. The proposed models, on the other hand, are the functions of network traffic parameters that can be gathered efficiently by parsing VoIP packets. Scatter plots in Figure 5.6 show the relationship between $MOS\text{-}LQO_{PESQ}$ and $MOS\text{-}LQO_{P.563}$ for G.729 and G.723.1 codecs.



(a) (b)

Figure 5.6: $MOS\text{-}LQO_{P.563}$ vs $MOS\text{-}LQO_{PESQ}$ for various VoIP network traffic conditions: (a) for G.729 and (b) for G.723.1

5.5 A Comparison with other Approaches

In this section the proposed methodology and the derived models are compared with the other parametric modeling approaches. A detailed comparison with every existing technique and result is difficult. Firstly, it is hard to reproduce the simulation results in exactly the same manner. Moreover, the nature of the training/testing data may affect the research results. Here, for instance, one research study may have assumed packet losses to be random (i.e. following a Bernoulli loss pattern) whereas another study may have assumed bursty losses. Similarly, the number of codecs employed can also have implications towards the performance of the derived models. Based on this a descriptive comparison is made between the proposed models and the existing studies.

Sun and Ifeachor [Sun and Ifeachor, 2006] and Rosenbluth [Cole and Rosenbluth, 2001] have proposed logarithmic functions to compute quality degradation functions. They assume that quality degrades logarithmically as a function of packet loss rate. There are two principal problems with their approach. First, it is obvious that for the chosen codecs the quality degradation is logarithmic with respect to the packet loss rate. However, this assumption may not hold for all codecs; the functional forms of codecs may differ from each other. Secondly, they have to tune two additional variables for each of the coding conditions e.g. for AMR-NB 7.4 and 12.2 (kbps) modes, two pairs of coefficients would have to be computed, which would then be stored in a look-up table or a database. Moreover, the performance results proposed by Sun and Ifeachor in [Sun and Ifeachor, 2006], despite appearing superior to ours, have been computed for the case of single coding conditions. Our results generalize for a wider range of distortion conditions.

Hoene et al. [Hoene et al., 2004] have employed a look-up table based approach for the derivation of their quality model. For a given codec they store the MOS

corresponding to certain values of packet loss rates. If during network operation, a value of packet loss rate that is not present in the look-up table is observed, linear interpolation is performed for known values to derive the result. In addition to the relative complexity of this approach compared to our proposal, the model is limited to the case of the AMR-NB codec only.

Sun and Ifeachor [Sun and Ifeachor, 2002a], Mohamed et al. [Mohamed et al., 2001] [Mohamed et al., 2004] have performed disparate research studies which employ ANNs to derive quality estimation models. A major problem with their approach, as in various ANN based models, is that a set of redundant variables has been used. Thus, for instance, [Sun and Ifeachor, 2002a] used *mbl* as an independent variable for the computation of the model. However, our research has shown that *mbl* is redundant. Our results are comparable to theirs. On the other hand, Mohamed et al. [Mohamed et al., 2001] [Mohamed et al., 2004] used subjectively estimated MOS as reference for model derivation. As discussed earlier, subjective estimates are superior to the results obtained through objective models such as PESQ. Their results are also seemingly superior to ours. However, there are a number of reasons for this. In their research they have only used 4–5 discrete values for packet loss rate. We have employed 12 values, allowing a finer granularity of data. Similarly, they employed a smaller number of network traffic configurations. Thus, for instance, where 112 different network configurations were simulated in [Mohamed et al., 2004], we used a total of *840* network operating conditions; an order of magnitude higher. This includes various combinations of *mlr*, *mbl*, and *br* etc. Consequently, a smaller number of data patterns were used both for training and testing. Given that subjective MOS were used as reference, it may be expected that there would be little variation in the results due to the prior *averaging*. Our research employs PESQ, which, for similar network distortion conditions, may exhibit high variance in results for different speech samples. Using PESQ as a reference, however, has the advantage that the results can

be repeated easily.

5.6 Conclusions

The problem of real-time quality estimation of VoIP is of significant interest. This chapter has shown an approach for solving this problem by employing GP. One of the main objectives of this research was to estimate the effect of burstiness on speech quality. It turned out that burst length was least used by the best individuals of various runs. This is due to the fact that the PESQ algorithm does not model the effect of burstiness on speech quality [Pennock, 2002] [Sun and Ifeachor, 2002b]. Hence, the effect of burstiness can be mapped only by conducting suitably designed formal subjective tests [ITU-T, 1996d]. Despite this limitation, PESQ is the best objective quality estimation model and has been used to model the effect of packet loss by various studies. The proposed models are good approximations to PESQ and computationally more efficient. Hence, they are useful for real-time call quality evaluation. For the codecs considered in this study, we have also proposed a model (equation(5.4.2)) that is a function of mlr_{VAD} only with performance comparable to the other models. This is significant since such a model can be deployed conveniently on a wide variety of platforms.

Our results are superior to the past research both in terms of performance and nature of the proposed models. For instance, Sun and Ifeachor [Sun and Ifeachor, 2002a] and Mohamed et. al. [Mohamed et al., 2001] [Mohamed et al., 2004] proposed ANN based models for VoIP quality estimation with the number of input parameters ranging between 4–5. However, a major limitation of ANNs is that the model interpretation remains an insurmountable proposition upon successful learning and, as a consequence, there is no direct method for estimating the significance of various input parameters. As stated earlier, evolutionary search prunes off the less significant

input parameters leading to simpler models proposed in this Chapter. Similarly, in their award winning paper Hoene et. al. [Hoene et al., 2004] present a look-up table based VoIP quality estimation model. The various MOS and corresponding parameter values would be stored in a lookup table. In the case the table does not contain a particular value of a parameter, linear interpolation is used to calculate MOS. Moreover, the model is not developed against a wider variety of input parameters. Although codec type is suggested as a network traffic variable in the abstract presentation of their VoIP quality estimation model, the number of codecs is actually restricted to 1 (i.e. AMR codec) in the model proposed therein. Our proposed models are free from such limitations. They can be used to assay the VoIP quality for any values of the input parameters which fall under the permissible range. Moreover, our models have been evolved against highly varying network conditions.

The focus of this chapter was on estimating speech quality of VoIP in an NB context. A followup of this research is presented in chapter 6 where equipment impairment factors are derived for the E-Model [ITU-T, 2005a] for a mixed narrowband/wideband (NB/WB) context, where distortion conditions due to both NB and WB codecs exist.

Chapter 6

A Methodology for Deriving VoIP Equipment Impairment Factors for a mixed NB/WB Context

6.1 Introduction

VoIP is curently evolving rapidly towards wideband based transmission. Wideband (WB) offers more natural sounding speech than narrowband (NB), and IP networks allow the transition to occur essentially by a simple change of codecs. It is clear, however, that there will be a transitional period, with wideband and narrowband VoIP coexisting, leading to a requirement for NB/WB interoperation. An important question that arises as a consequence is how is the quality of such a mixed NB/WB system to be estimated?

VoIP quality is affected by various factors such as packet loss, end-to-end delay, jitter and codec bit-rate etc. A number of approaches and models exist that estimate speech quality as a function of such impairments. Of particular interest among these is ITU-T Recommendation G.107 [ITU-T, 2005a], commonly known as the E-Model, which is an instrumental model that was initially designed for transmission planning

purposes. It is based on an impairment factor principle that assumes that the degradations induced by various sources have a cumulative effect on speech quality and that they may accordingly be transformed to a *transmission rating scale (R scale)*. The E-Model was originally intended for NB speech quality estimation. Recently, in [Möller et al., 2006], Möller et al. proposed an extension of the R scale to incorporate WB codecs into E-Model, while leaving the original R scale for the NB case intact. Their main emphasis has been on deriving *equipment impairment factors* ($I_{e,WB}$), in a mixed NB/WB context, that represent the degradation in the *listening quality* of speech in the wake of pure codec related distortions. Their derivation is based on subjective *listening only* tests [ITU-T, 1996c] for a mixture of various NB and WB codecs defined by ITU-T.

In the past several authors have taken different approaches towards deriving *effective equipment impairment factors* ($I_{e,eff}$) for NB codecs. Effective equipment impairment factors correspond to combined impairments due to packet loss and codec. In this research a novel perspective was taken towards deriving effective equipment impairment factors for the *mixed NB/WB* case i.e., $I_{e,WB,eff}$. Here the novelty is twofold. First, we propose to use instrumental models as a means to derive reference $I_{e,WB,eff}$, as opposed to subjective tests. Secondly, the mapping between various quality affecting parameters and reference $I_{e,WB,eff}$ is achieved by employing Genetic Programming (GP) based symbolic regression [Koza, 1992]. This approach is based on the work reported in Chapter 5 (and also in [Raja et al., 2006] and [Raja et al., 2007]) where GP was used to derive parsimonious speech quality estimation models.

In this research a number of state-of-the-art VoIP telephony codecs proposed by ITU-T have been employed. ITU-T P.862.2 (i.e.WB-PESQ), as reported in [ITU-T, 2005f], has been used as a reference system. We follow the methodology described in [ITU-T, 2002] for deriving $I_{e,eff}$ and propose ours as an addendum to it for deriving $I_{e,WB,eff}$.

The rest of this chapter is organised as follows. In section 6.2 the E-model framework is described. There we highlight past attempts by various researchers in deriving $I_{e,eff}$ and $I_{e,WB,eff}$ and present our approach too. Section 6.3 discusses the factors that affect $I_{e,WB,eff}$. Section 6.4 elucidates the proposed methodology in detail along with the VoIP simulation system describing various NB and WB codecs used in this research and the data processing procedures. Details of GP experiments, various results and models are discussed in section 6.5. Finally, section 6.6 concludes this chapter.

6.2 The E-Model

The E-Model, as defined by ITU-T G.107 [ITU-T, 2005a], is a computational model used for assessing the combined effect of various parameters on speech quality in a conversational sense. Initially it was designed for NB handset telephony, however, its adaptation to the WB case is currently in progress. The primary output of the model is the *Rating Factor*, R. The derivation of R is based on an impairment factor principle that assumes that factors affecting speech quality are additive in nature. Thus, R is computed according to equation (6.2.1):

$$R = R_0 - I_s - I_d - I_{e,eff} + A \tag{6.2.1}$$

where R ranges from 0 (poor quality) to 100 (optimum quality) for the NB case. R_0 is the basic signal to noise ratio which, for the NB case, defaults to 93.2. I_s represents all the impairments which occur simultaneously with the voice including, for instance, overall loudness rating and non-optimum sidetone. I_d marks the effect of delay related impairments such as echo and too long end-to-end delay that may affect the call quality in a conversational sense. $I_{e,eff}$ depicts the impairments due to low bit-rate codecs in the presence of packet losses. Finally, A is the advantage factor

that compensates for the above impairment factors when there are other advantages of access to the user depending on the nature of the underlying network. Thus, for instance, A may be assigned a value of 0 for a wired network and 20 for a multi-hop satellite connection. In the case where values of one or more of these factors may not be determined, default values are used from [ITU-T, 2005a]. Thus, the advantage factor may be thought to be a convenience whereby the user may be more forgiving on quality.

R can be converted to *Mean Opinion Score (MOS)* and vice versa using corresponding transformations given in [ITU-T, 2005a]. Since we have leveraged from these transformations in this research we shall refer to them by an abstract notation given by transformation (6.2.2). The related pair of equations is given in appendix A for perusal.

$$R \Longleftrightarrow MOS \tag{6.2.2}$$

where MOS varies on a scale ranging between 1 (bad) to 4.5 (excellent), and it is a measure of human assessment of speech quality. The relationship between MOS and R is shown in Figure 6.1 with the solid curve.

The above formulations hold for the case of NB codecs. In [Möller et al., 2006] Möller et al. proposed a transformation of the R scale from the NB case (R_{NB}) to the mixed NB/WB case ($R_{NB/WB}$) based on subjective tests performed in [Barriac et al., 2004]. The test results suggest that for the scenario where only NB coded samples were present, MOS scores were higher than those for the same samples evaluated in presence of additional, objectively better, WB coded stimuli. Moreover, since the MOS to R conversion represented by transformation (6.2.2) was applied, the R_{NB}, for the NB context, turned out to be higher than $R_{NB/WB}$ for the mixed NB/WB context. This would have repercussions for the validity of the original R scale in a mixed NB/WB context as it would affect the NB usage of the scale. Thus, an

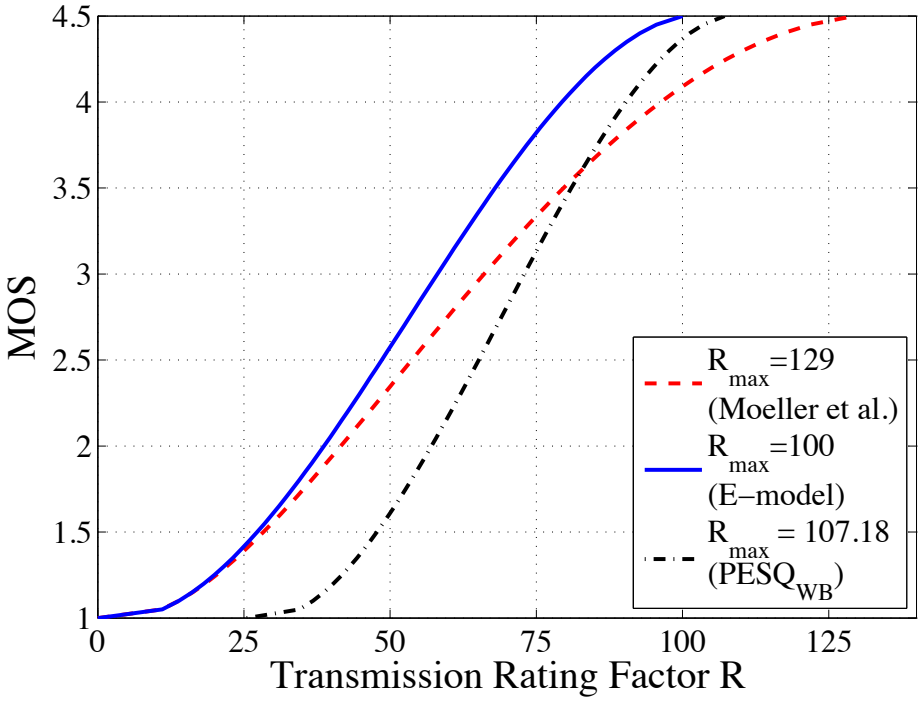


Figure 6.1: Transformation rules between R and MOS. Solid line: NB case of the E-Model, dashed line, NB/WB case (Möller et al.) and dashed-dotted line forWB-PESQ

extension of the R scale for the NB/WB case was proposed that leaves the original R scale for the NB context unaltered. This extension is given by equation (6.2.3)[1].

$$R_{new} = a.\left(e^{R_{NB/WB}/b} - 1\right) \tag{6.2.3}$$

where a and b were found to be equal to 169.38 and 176.32 respectively, and $R_{NB/WB}$ can be calculated via (6.2.2). This extension is now an integral part of the E-Model (see Appendix II of [ITU-T, 2005a]), where the new default value for R_0 for the NB/WB case is 129. Following this, $I_{e,WB}$ (i.e. impairments solely due to various

[1]A linear version of this extension also exists that has been skipped for brevity

low bit-rate NB/WB codecs) can be calculated according to equation (6.2.4) as a difference between R-value of the *direct* channel and R-value corresponding to the codec under consideration.

$$I_{e,WB} = 129 - R_{codec} \tag{6.2.4}$$

where R_{codec} may be calculated from (6.2.3) and 129 corresponds to the value of R for the direct channel for the mixed NB/WB context. The direct channel in this context is represented by a 16-bit linear PCM with f_s=16 kHz (this also assumes that impairments due to other factors such as echo or delay are not present).

6.2.1 On Extending the R scale for WB-PESQ

Our work employs WB-PESQ as a reference for deriving $I_{e,WB}$ and $I_{e,WB,eff}$, as opposed to subjective tests. A WB version of R scale does not exist in the literature for WB-PESQ. There can be two approaches in principle to convert MOS-LQO *(MOS-Listening Quality Objective)* [ITU-T, 2003b] obtained by WB-PESQ to the R scale. Both of these are discussed in this section.

1) One approach may be to extend the R scale using MOS-LQO obtained by WB-PESQ using the methodology proposed in [Möller et al., 2006] by Möller et al; as has been previously discussed. Based on this an experiment was performed to see whether a meaningful extension of the R scale could be made for WB-PESQ. Two test cases were prepared, each comprising 1328 pairs of reference and *coded* file pairs of experiments 1 and 3 of the ITU-T P-series supplement 23 [ITU-T, 1998a]. The coded files contain various NB scenarios with distortion conditions such as low bit-rate coding, signal correlated noise, codec tandeming, bit errors and frame erasures. Conditions representing direct *(or clean)* NB channel are also present. All the files are originally coded in 16-bit linear PCM format, f_s=16 kHz. The file pairs in the

first test case were evaluated with WB-PESQ. This constitutes the WB (or NB/WB) context with WB coded references and NB coded and upsampled test files. File pairs in the second test case were evaluated with NB-PESQ. To this end, all the reference and coded files were downsampled and low-pass filtered using [ITU-T, 2005e] prior to evaluation. This corresponds to an NB test.

The resulting scatter plot for R_{NB} and $R_{NB/WB}$ is displayed in Figure 6.2. The data was fitted using least squares regression where a linear relationship of the form of equation (6.2.5) was used.

$$R_{NB} = a.R_{NB/WB} + b \tag{6.2.5}$$

where, a=0.82, b=25.46 and $RMSE$=4.12.

According to this R_{max} was found to be 107.18. This suggests a rather small extension of the R-scale; only a 7% gain in quality due to WB coded speech. The new curve is drawn in Figure 6.1 with a dashed-dotted line.

It is worth mentioning here that WB-PESQ has a number of limitations. First of all, the restricted set of training and testing databases limits the reliability of WB-PESQ in comparison with NB-PESQ. Language and codec dependence is another limitation of the algorithm [Raake, 2006, pp-105] [Morioka et al., 2004]. It was also observed that WB-PESQ systematically underestimates speech quality in comparison with subjective tests. This was observed from a comparison made between MOS-LQO obtained by WB-PESQ and MOS-LQS *(MOS-Listening Quality Subjective)*. The results of the comparison are shown in Figure 6.3. Here the MOS-LQS were obtained by performing $I_{e,WB}$ to MOS conversion for codecs under consideration using equations (6.2.4), (6.2.6)[2] and (6.2.2). Values of $I_{e,WB}$ were taken from [ITU-T, 2006b].

[2]Equation (6.2.6) is the inverse of equation (6.2.3)

$$R_{orig} = ln\left(\frac{R_{new} + 169.38}{169.38}\right) \times 176.32 \tag{6.2.6}$$

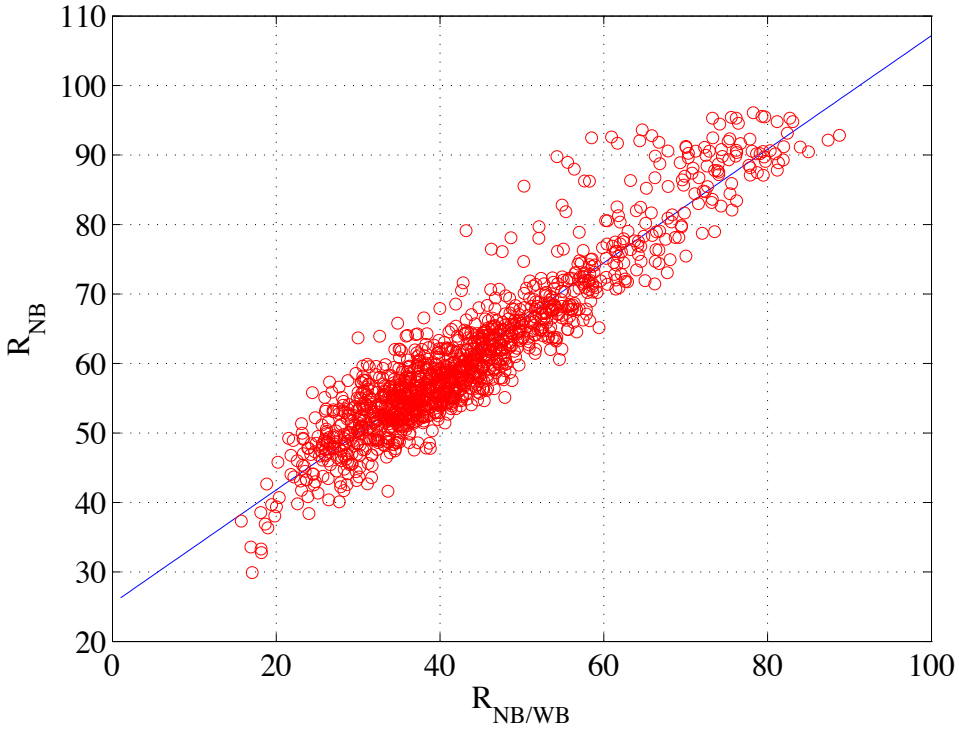


Figure 6.2: Comparison between R-values obtained from a NB and a mixed NB/WB context using PESQ.

2) The second approach is to convert the MOS-LQO to the R scale using equations (6.2.2) and (6.2.3), in the order given. This is analogous to the methodology given in ITU-T P.834 [ITU-T, 2002]. As there are clear problems associated with reconciling the R scale in the case of subjective and objective tests, as seen during the analysis of first approach, we have chosen the second approach. This is used to derive reference values of $I_{e,WB,eff}$ in this research. We argue that our methodology would not be affected due to changes in the mathematical form of any R scale extension; the

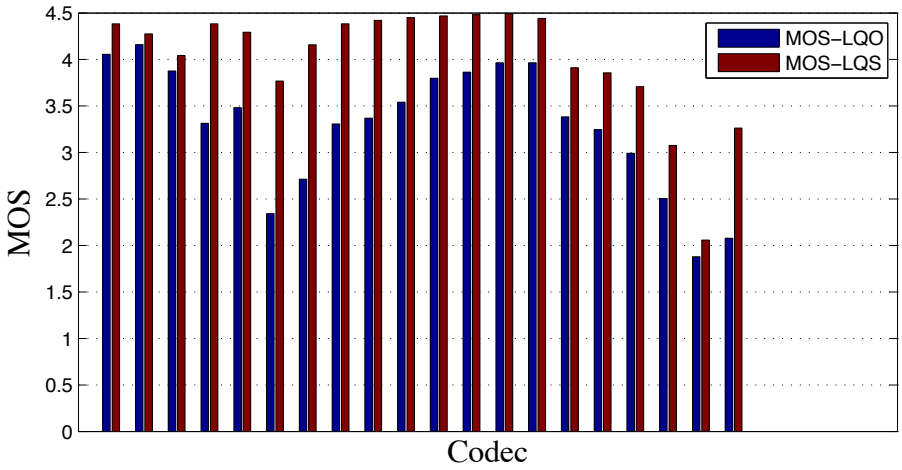


Figure 6.3: Comparison between MOS-LQO and MOS-LQS for various NB and WB codecs

experiments that follow can be conveniently repeated for a new *(target)* R scale.

6.3 $I_{e,WB,eff}$ and Associated Quality Elements

According to the E-Model [ITU-T, 2005a] $I_{e,eff}$ for a given NB codec may be computed from

$$I_{e,eff} = I_e + (95 - I_e) \times \frac{P_{pl}}{\frac{P_{pl}}{BurstR} + Bpl} \tag{6.3.1}$$

where, I_e is the impairment factor for the codec under consideration in the case of no packet loss. P_{pl} is the packet loss rate (%). BurstR is the Burst Ratio; discussed below. Bpl is the packet loss robustness factor for the codec under consideration. It describes the the robustness of the codec, including the employed packet loss concealment mechanism, against packet loss. A similar formulation for $I_{e,WB,eff}$ is given in [Möller et al., 2006] for *random* packet loss.

Given this, $I_{e,WB,eff}$, or equivalently $I_{e,eff}$, depends on two quality elements, namely *packet loss* and *codec*. In the text that follows various aspects of these two elements are discussed in detail.

6.3.1 Packet Loss

Packet loss may either be random, where loss patterns follow a Bernoulli-like distribution, or bursty in nature. In bursty loss, a lost packet tends to exhibit a temporal dependency on its immediately preceding (lost or arrived) packet, or past n packets [Raake, 2006] [Sanneck and Carle, 2000] [Jiang and Schulzrinne, 2000] [Clark, 2001]. E-Model defines a $BurstR$ parameter (*Burst Ratio*) where burstiness is modeled using a two-state Markov model, with a loss and a no-loss state, and with two transition probabilities associated with each state.

Another factor affecting quality impairment, and closely associated with packet loss, is the packetization interval (PI) (ms), i.e., the payload size of an IP packet. In order to utilize the transmission bandwidth effectively, it is desirable to increase the PI. However, larger values of PI result in larger transmission delay and possibly lower speech quality in the event of a packet loss. Current VoIP applications use values of PI ranging between 10–60 ms as a compromise [Raake, 2006].

The problems associated with packet loss may be circumvented to a certain extent with various *packet loss recovery* methods such as Forward Error Correction, Low-bit-rate Redundancy and Packet Loss Concealment (PLC) [Perkins et al., 1998].

6.3.2 Codec

$I_{e,WB,eff}$ is a codec specific quantity and thus dependent on it. A speech codec may either belong to the class of *waveform* coders, parametric coders or hybrid coders i.e. a combination of the first two. Waveform coders perform quantization of the speech

signal and parametric coders employ a suitable speech production model for reducing bandwidth requirement for speech transmission [Chu, 2003]. For a given class of coders the speech quality may further depend on factors such as codec's bit-rate, frame size and coding algorithm. The codec's transmission bandwidth (i.e. NB or WB) also affects the quality perceived by the user. Thus WB codecs deliver better quality than their NB counterparts mainly because of the increased naturalness of speech due to the presence of higher order spectral components [Möller et al., 2006] [Raake, 2006].

In the past various authors have tried to model speech quality as a function of coding bit-rate (in addition to loss metrics) e.g. [Sun and Ifeachor, 2002a] [Mohamed et al., 2004] [Hoene et al., 2005] and also by the authors in [Raja et al., 2006] [Raja et al., 2007]. It may be argued that although coding bit-rate may be used as a quality defining parameter for general predictions, it may not be able to give accurate predictions due to two main reasons.

First, in the absence of any other impairments two different codecs, with differing bit-rates, may deliver the same quality to users; e.g. G.722 [ITU-T, 1988a] (64 kbps), G.722.1 [ITU-T, 2005b] (32 kbps) G.722.2 [ITU-T, 2003d] (12.65 kbps) have their $I_{e,WB}$ equal to 13 [ITU-T, 2006b].

Secondly, a high degradation of quality may be associated with a codec with low I_e (or $I_{e,WB}$) in the presence of packet loss. An example of this may be AMR-NB (12.2 kbps) and iLBC (15.2 kbps); the former offers a better quality in the absence of packet losses, whereas the latter outperforms in the presence of losses [Sun and Ifeachor, 2006]. This behavior is due to the *robustness of a codec against packet loss* and may depend on several factors such as , loss distribution (random or bursty), type of packet loss recovery algorithm employed by the codec and the time taken by a decoder's state to resynchronize with that of the coder in the event of packet loss [Rosenberg, 2001].

This reflects the interpretation that codec-related effects on $I_{e,WB,eff}$ may be due

to $I_{e,WB}$ and the robustness of that codec against packet loss.

6.3.3 Discussion

The E-Model uses two predefined parameters to compute $I_{e,eff}$; namely I_e and Bpl (packet loss robustness factor) along with packet loss statistics as in equation (6.3.1). The significance of these parameters has been discussed in section 6.3.2. Similarly, in [Cole and Rosenbluth, 2001] Cole and Rosenbluth and in [Sun and Ifeachor, 2006] Sun and Ifeachor have proposed a logarithmic function of the form:

$$I_{e,eff} = x_1 + x_2 \times ln(1 + x_3 \times mlr) \tag{6.3.2}$$

where they tune x_i to compute the codec specific $I_{e,eff}$ as a function of *mean packet loss rate* (mlr). It may be argued that their formulation of $I_{e,eff}$ depends on I_e (i.e. when mlr=0) and packet loss robustness, which translates into parameters x_2 and x_3.

Janssen et al. have depicted a relationship between codec specific $I_{e,eff}$ and packet loss rate in the form of quadratic curves [Janssen et al., 2002].

It follows that different codecs may have different curves for $I_{e,WB,eff}$. This effect may be seen in Figure 6.4. Here, for example, $I_{e,WB,eff}$ for the *Adaptive Multi-Rate-NB (AMR-NB)* [ETSI, 2000] codec (7.4 kbps) may be approximated with a logarithmic curve (equation (6.3.2)), whereas the best fit curve for G.722.2 (19.85 kbps) was found to be a 4^{th} order polynomial.

It is clear that currently there is no widely accepted and *clearly superior* formulation for $I_{e,WB,eff}$. We suggest an alternative, altogether different, strategy. Instead of approaching the problem with *a priori* assumptions about the analytical form of $I_{e,WB,eff}$, we allow the data to speak for themselves. We propose to *evolve* high-quality expressions for $I_{e,WB,eff}$ using GP.

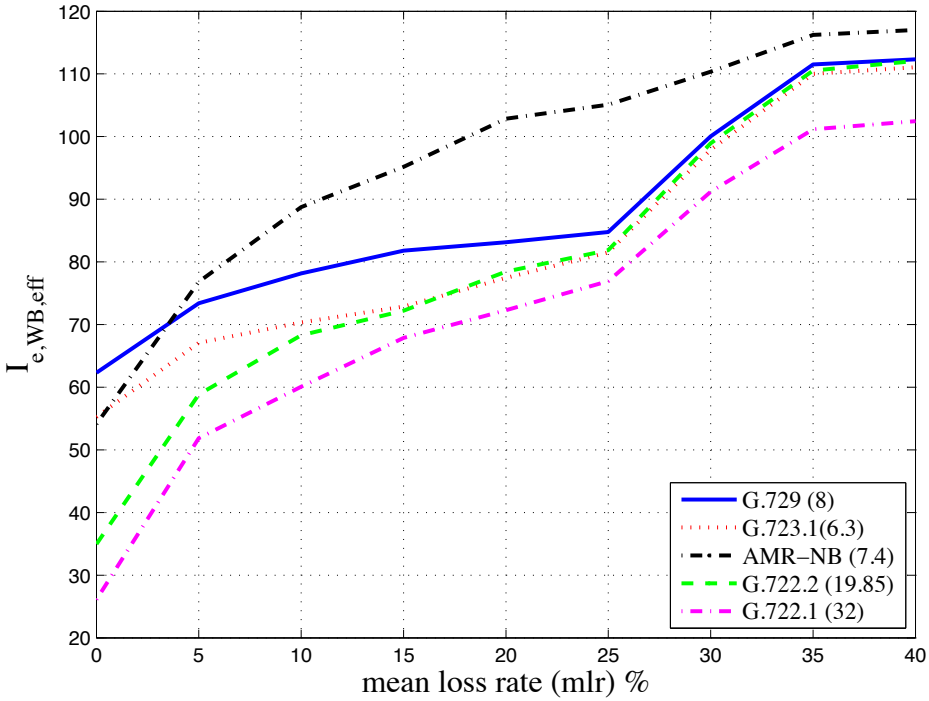


Figure 6.4: $I_{e,WB,eff}$ as a function of mlr for various NB/WB codecs. values for $I_{e,WB,eff}$ were computed using WB-PESQ with random packet loss and PIs equal to one speech frame of the respective codecs.

6.4 The new Methodology

In what follows we first describe our methodology for deriving $I_{e,WB,eff}$ as a function of VoIP traffic parameters. Next, we list the details of our data preparation procedure and of the VoIP simulations undertaken.

6.4.1 Methodology

This methodology is based on the research presented in 5 (and in [Raja et al., 2006] and [Raja et al., 2007]), with the main difference being that there the objective

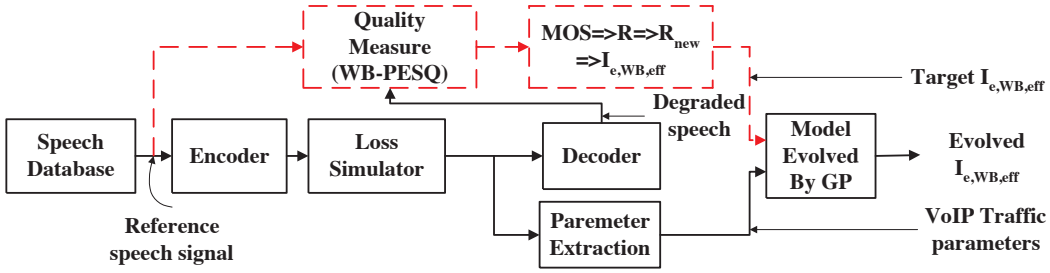


Figure 6.5: Simulation system for derivation of $I_{e,WB,eff}$

was to compute MOS for an NB context whereas here the main focus is on deriving equipment impairment factors, $I_{e,WB,eff}$, for a mixed NB/WB context. The schematic in Figure 6.5 depicts a conceptual diagram of our approach for deriving $I_{e,WB,eff}$ for VoIP. An initial requirement is to have a database consisting of clean speech signals. These signals are subjected to degradations typical of VoIP traffic; coding distortions and packet loss. The degraded VoIP stream is eventually converted back to linear PCM format using a decoder corresponding to the encoder. In the process of doing so the values of various VoIP traffic parameters, such as packet loss rate, are calculated and the decoded speech signal is sent to a viable instrumental model that may report its results in terms of human assessment of speech quality i.e. MOS-LQO. Moreover, the model should be able to evaluate both NB and WB coded speech. An example of such a model is WB-PESQ, which has been used as a reference system in this research. The resulting MOS-LQO is converted to $I_{e,WB,eff}$ using equations (6.2.2), (6.2.3) and eventually (6.2.4). We call this the *target* $I_{e,WB,eff}$. The process is repeated for a large number of speech signals with varying degrees of network distortion conditions. Once the target $I_{e,WB,eff}$ for all the speech signals have been computed and the values of corresponding VoIP network traffic parameters gathered, GP based evolution is performed to derive a suitable mapping. More specifically, the VoIP network traffic parameters serve as the input domain variables during evolution

and the corresponding $I_{e,WB,eff}$ values form the *target* output values.

A linear interpolation between the $I_{e,WB}$ obtained by the instrumental model (WB-PESQ) and subjective tests may be performed as suggested by ITU-T P.834 [ITU-T, 2002, pp-9] to adjust the target $I_{e,WB,eff}$. To this end, interpolation was performed between $I_{e,WB}$ values for 20 (14 WB and 6 NB) codecs obtained using WB-PESQ, and from subjective tests reported in [ITU-T, 2006b]. Here, for each codec, $I_{e,WB}$ corresponding to WB-PESQ was obtained by averaging the evaluations of 30 speech file pairs. Clean speech files were taken from experiment-1 of [ITU-T, 1998a]. The slope and intercept were found to be equal to 0.6730 and 35.7881 respectively. It must be noted that a large intercept indicates an experimental bias [ITU-T, 2001a, pp12]. This is possibly due to the fact that WB-PESQ underestimates the speech quality as compared with subjective tests, as discussed in section 6.2.1.

6.4.2 Input Domain Variables

mlr, PI and *mean burst length* (mbl) were chosen as the input domain variables related to packet loss. $I_{e,WB}$ and a *coarse* estimate of loss robustness factor were computed for each codec separately as other independent parameters. It was expected of GP to make efficient use of these parameters during evolution. It was discussed in section 6.3.3, and shown in Figure 6.4, that the functional form of $I_{e,WB,eff}$ may vary for different schemes and codecs. Given this, the gradient of $I_{e,WB,eff}$ for mlr ranging between 0–0.3 was computed according to equation (6.4.1) as a *coarse* estimate of packet loss robustness factor, assuming that GP would use it effectively during evolution. This range of mlr is chosen because $I_{e,WB,eff}$ varies the most for mlr=0.0–0.3. After this the change is only gradual, as can be seen from Figure 6.4. Moreover, the data presented by Sun and Ifeachor [Sun and Ifeachor, 2006] imply the same for $I_{e,eff}$, where maximum mlr=0.3.

$$grad = \frac{I_{e,WB,eff}(mlr = 0.3) - I_{e,WB,eff}(mlr = 0.0)}{0.3} \tag{6.4.1}$$

Values of $I_{e,WB}$ and gradients of $I_{e,WB,eff}$ with respect to mlr for the codecs under consideration are listed in Table. 6.1.

Table 6.1: Values for $I_{e,WB}$ and coarse estimates of loss robustness factor

Codec	bit-rate	$I_{e,WB}$	gradient
G.722.1	32	26.12	216.88
G.722.1	24	29.04	208.36
G.722.2	6.6	68.13	104.25
G.722.2	8.85	58.64	139.67
G.722.2	12.65	43.91	187.62
G.722.2	14.25	41.19	196.13
G.722.2	15.85	39.59	201.50
G.722.2	18.25	36.09	212.81
G.722.2	19.85	34.97	213.20
G.722.2	23.05	32.09	225.27
G.722.2	23.85	33.88	221.27
G.729	8	62.33	125.66
G.723.1	6.3	55.27	142.14
AMR-NB	7.4	63.9	151.30
AMR-NB	12.2	54.12	187.48

6.4.3 VoIP Simulation

A simulation based approach was pursued in this research, where distortions typical of a VoIP network were induced on a large number of clean speech signals before decoding the corresponding coded bitstreams. Clean speech samples from experiments 1-A and 1-D of ITU-T P-series supplement 23 were used. The NB codecs include: ITU-T G.729 CS-ACELP (8 kbps) [ITU-T, 1996a], ITU-T G.723.1 MP-MLQ/ACELP (5.3/6.3 kbps) [ITU-T, 1996b] and AMR-NB codec [ETSI, 2000]. AMR-NB was used in its 6.7 and 12.2 kbps modes whereas G.723.1 was used in its 6.3 kbps mode.

The WB codecs include ITU-T G.722.1 [ITU-T, 2005b] (24/32 kbps) and ITU-T G.722.2 [ITU-T, 2003d], *Adaptive Multi-Rate (AMR-WB)* codec. AMR-WB can operate in 9 different coding/decoding modes, each targeting a different bit-rate: all the coding modes were utilized in this research.

Various network traffic simulation conditions were chosen in the light of ITU-T Recommendation G.1050 [ITU-T, 2005c], which specifies a model for evaluating multimedia transmission performance over an IP network. Bursty packet loss was emulated using a 2-state Markov model; with probabilities p, for transitioning from a no-loss state to a loss state and q, for the converse. It was assumed that *jitter* also maps to packet loss and that it can be modeled using this 2-state model as in [Sun and Ifeachor, 2002a]. Packet loss for twelve different values of (target) *mlr* was simulated; [0,2.5,..., 15, 20, ..., 40]%. For each value of *mlr*, *conditional loss probability (clp) (i.e. 1-q)* was set to 10, 50, 60, 70 and 80%. It is worth mentioning that higher values of *clp* model higher degrees of loss burstiness and vice versa. Moreover, PI (packetization interval) was varied between 10–60 ms.

Since the clean speech samples are coded at a 16 kHz sampling rate, they were downsampled before encoding in the case of NB codecs. Subsequently, the corresponding decoded speech samples were upsampled before evaluation by WB-PESQ.

In all, 2,820 combinations of network distortion conditions were emulated. A given combination of network distortion conditions was applied to four speech samples. Moreover, each speech sample under consideration was subjected to the same combination of network distortion conditions 30 times to produce as many test samples by pseudo-randomly generating different loss patterns each time. This was done to negate the effect of packet loss locations as in [Sun and Ifeachor, 2006] by eventually aggregating the MOS for all test samples corresponding to one source sample. Thus, a total of 338,400 distorted speech files were created. These distorted speech files were subsequently evaluated by WB-PESQ on a Beowulf cluster with respect

to corresponding reference files. Values of the network traffic parameters for all files and the corresponding MOS were averaged to form a total of 11,280 input/output patterns, that would later be utilised during symbolic regression.

6.5 Experiments and results

6.5.1 Experimental Details

Two GP experiments were performed to evolve models for $I_{e,WB,eff}$ using the input/output data patterns. The accumulation of data patterns has already been discussed in section 6.4.3. GPLab was used for evolution. Previously in Chapter 5 ([Raja et al., 2007]) we performed four GP experiments with different maximum tree depths and error measures with different results. In this work we chose the experimental conditions that produced superior results in terms of quality to perform the two GP experiments. The common parameters of both experiments are listed in Table 6.2.

In both experiments scaled mean squared error (MSE_s) was used as the fitness criterion discussed earlier in section 4.3 and given by equation (6.5.1).

$$MSE_s(y,t) = 1/n \sum_{i}^{n} (t_i - (a + by_i))^2 \tag{6.5.1}$$

where y is a GP evolved function of the input parameters in this case (a mathematical expression), y_i represents the output value produced by y for the input case i and t_i represents the corresponding target value of $I_{e,WB,eff}$. a and b adjust the slope and y-intercept of the evolved expression to minimise the squared error.

Tournament selection with Lexicographic Parsimony Pressure (LPP) [Luke and Panait, 2002] was used in both experiments. Moreover, the selection criteria in both the experiments was also adapted to the one proposed by Gustafson et al.

Table 6.2: Common GP Parameters among all experiments

Parameter	**Value**
Initial Population Size	300
Initial Tree Depth	6
Selection	LPP
Tournament Size	2
Genetic Operators	Crossover and Subtree Mutation
Operators Probability Type	Adaptive
Initial Operator probabilities	0.5 each
Survival	Half Elitism
Generation Gap	1
Function Set	plus, minus, multiply, divide,sin, cos, log_2, log_{10}, log_e, sqrt, power
Terminal Set	Random real-valued numbers between 0.0 and 1.0. Integers (2-10). mlr, mbl, PI, $I_{e,WB}$, $grad$

in [Gustafson et al., 2005] for symbolic regression problems.

Whenever input values outside the domain of the functions *log, sqrt, division* and *pow* are encountered, NaN (undefined) values are generated. This results in the individual concerned being assigned the worst possible fitness value and minimising its chances of being selected as a parent.

As mentioned in section 4.1, it is typical to conduct several independent runs of GP. In this case, both experiments entailed 50 independent runs each spanning 50 generations.

The only difference between the two experiments was that in the first experiment the maximum tree depth was 17. This was reduced to 7 in the second experiment to see if parsimonious individuals with performance comparable to those of the first experiment can be obtained.

6.5.2 Results and Analysis

Of 11,280 input/output patterns reported in section 6.4.3, 1,440 patterns corresponding to AMR-NB 7.4 kbps and G.722.1 32 kbps were separated for model validation on *unseen* codecs. Of the remaining 9,840 patterns, 70% were used for training and 30% for testing the evolved models. Various VoIP traffic parameters have been discussed in section 6.4.3. More specifically, these include, $I_{e,WB}$, mlr, PI, mean burst length (mbl) and $grad$, as in equation (6.4.1), as a coarse estimate of codec specific loss robustness factor.

The statistics pertaining to $RMSE_s$ (square root of the scaled MSE) of training and testing data of both GP experiments are listed in Table 6.3(a). The table also lists various statistics related to the tree sizes of GP individuals, in terms of the number of nodes. The results of both experiments in the final generations were also treated to a Mann-Whitney Wilcoxon test to assay the significance of differences in various respects. The significance analysis is reported in Table 6.3(b) where a value of '1' confirms a significant difference, at a 5% confidence level, whereas a '0' implies otherwise. It was found that the overall results of the two experiments are not significantly different from each other in terms of fitness over training and testing data. However, the difference in terms of tree size is significant, with experiment 2 having individuals with smaller trees.

It is also worth mentioning here that the best individuals resulting from three runs of experiment 1 were treated as over-fit due to their very large $RMSE_s$ over the testing data, ranging between 650–10,000, and were subsequently removed from the analysis.

In this chapter we present three models resulting from the experiments. Two of these correspond to individuals with minimum $RMSE_s$ over the testing data in each of the experiments. These are represented by equations (6.5.2) and (6.5.3) and they

Table 6.3: Statistical analysis of the GP experiments and derived models

(a) MSE Statistics for Best Individuals of 50 Runs for Experiments 1 & 2

	$Experiment1$			$Experiment2$		
Stats	$RMSE_{tr}$	$RMSE_{te}$	$Size$	$RMSE_{tr}$	$RMSE_{te}$	$Size$
Mean	8.9478	32.5851	28.3617	8.9861	23.9743	19.02
Dev.	0.1890	113.2837	12.2144	0.2740	105.2397	6.3326
Max.	9.3624	655.5639	77	9.8275	753.2457	38
Min.	8.3941	8.5057	13	8.3552	8.4605	10

(b) Results of Mann-Whitney-Wilcoxon Significance Test

	$Experiment1$		
	$RMSE_{tr}$	$RMSE_{te}$	$Size$
$Experiment2$	0	0	1

(c) Performance Statistics of the Proposed Models

	Training			**Testing**		
Model	$RMSE_s$ MOS	$RMSE_s$ $I_{e,WB,eff}$	σ	$RMSE_s$ MOS	$RMSE_s$ $I_{e,WB,eff}$	σ
Equation (6.5.2)	0.0990	8.3941	0.9236	0.1007	8.5057	0.9240
Equation (6.5.3)	0.0975	8.3552	0.9243	0.0990	8.4605	0.9248
Equation (6.5.4)	0.1183	9.1749	0.9080	0.1207	9.3145	0.9080

belong to experiments 1 and 2 respectively. The third model, represented by equation (6.5.4) corresponds to the most parsimonious individual of both the experiments and is derived from experiment 2.

$$I_{e,WB,eff} = \{11 - mbl + ln(grad) + grad \times mlr + I_{e,WB} - 2.log_2(PI)\} \times 0.8619 + 9 \tag{6.5.2}$$

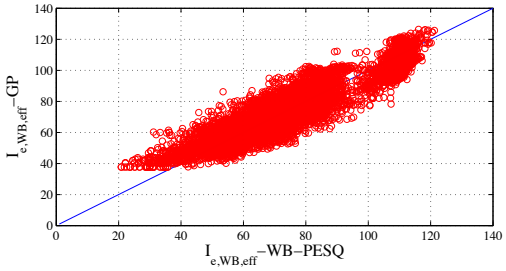
$$I_{e,WB,eff} = \left\{ ln\left(\frac{9 \times (I_{e,WB} + mlr \times grad^2)}{mbl^5 - mlr}\right) + mlr + I_{e,WB} + grad \times mlr \right\} \times 0.8303 + 8.9977 \tag{6.5.3}$$

$$I_{e,WB,eff} = (log_{10}(log_{10}(log_2(I_{e,WB} - 2 \times mbl) + mlr))) \times 321.7017 + 95.3708 \tag{6.5.4}$$

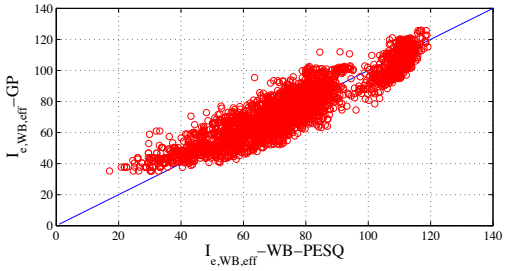
The $RMSE_s$ and Pearson's product moment correlation coefficient (σ), corresponding to $I_{e,WB,eff}$ for these models are compared with each other in Table 6.3(c). The values of $RMSE_s$ corresponding to *MOS-LQO* are also listed as another comparison. These were computed by converting the target values of $I_{e,WB,eff}$ and those obtained by the models under consideration to the MOS scale. This may be done by obtaining the values of R corresponding to $I_{e,WB,eff}$ from equation (6.2.4). The result can then be transformed to the original R scale for the NB-only context using equation (6.2.6); the inverse of equation (6.2.3). The resulting values of R can be

converted to the MOS scale using transformation (6.2.2). The significance of all of the models can be judged by observing that the values of $RMSE_s$ on the MOS scale in all cases range between 0.098–0.12. This presents a considerably minute difference for a human subject to detect.

Equation (6.5.3) has the best statistics among all. Figure 6.6 shows the scatter plots of equation (6.5.3) versus WB-PESQ, where it can be seen that the data points produced by both are firmly glued to the 45 degrees reference line.



(a)



(b)

Figure 6.6: $I_{e,WB,eff}$ predicted by equation (6.5.3) vs target $I_{e,WB,eff}$ for: (a) training data (b) testing data

A significance analysis of the various VoIP traffic parameters, in terms of their appearance in the best individuals of 50 runs of each of the two experiments, was done. The results are graphed in Figure 6.7. According to this $I_{e,WB}$ and mlr had the highest utility, and appeared in 92–94% of the individuals. The third most

significant parameter was *grad*, appearing in 36–38% of the best individuals of both experiments. *mbl* appeared in between 24–26% whereas, PI appeared in only 12% of the best individuals. The last two observations have also been reported by other researchers, such as [Sun and Ifeachor, 2002b] [Pennock, 2002], who note that PESQ does not model the effect of burstiness on speech quality. We reported similar results in Chapter 5 and in [Raja et al., 2006]. Figure 6.8 illustrates similar behavior, but for WB-PESQ and a WB codec (AMR-WB 23.85 kbps). It is obvious that a correlation between $I_{e,WB,eff}$ and *mbl* does not exist. A similar comparison for the case of G.729 is shown in Figure 6.9 where absence of any correlation between $I_{e,WB,eff}$ and PI may also be observed.

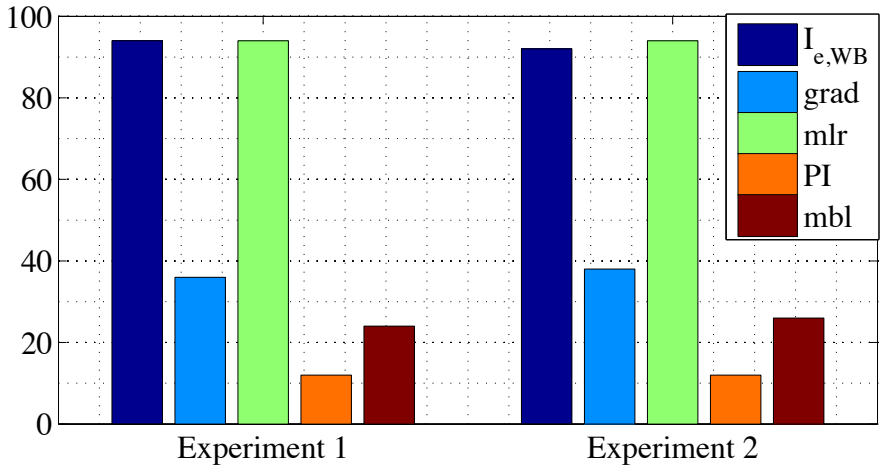


Figure 6.7: Percentage of the best individuals employing various input parameters in acceptable runs of each of the two experiments.

6.5.3 Comparison with the E-Model

Finally, a comparison of equation (6.5.3) was made with the E-Model's formulation of the $I_{e,WB,eff}$, as in [Möller et al., 2006]. This is represented by:

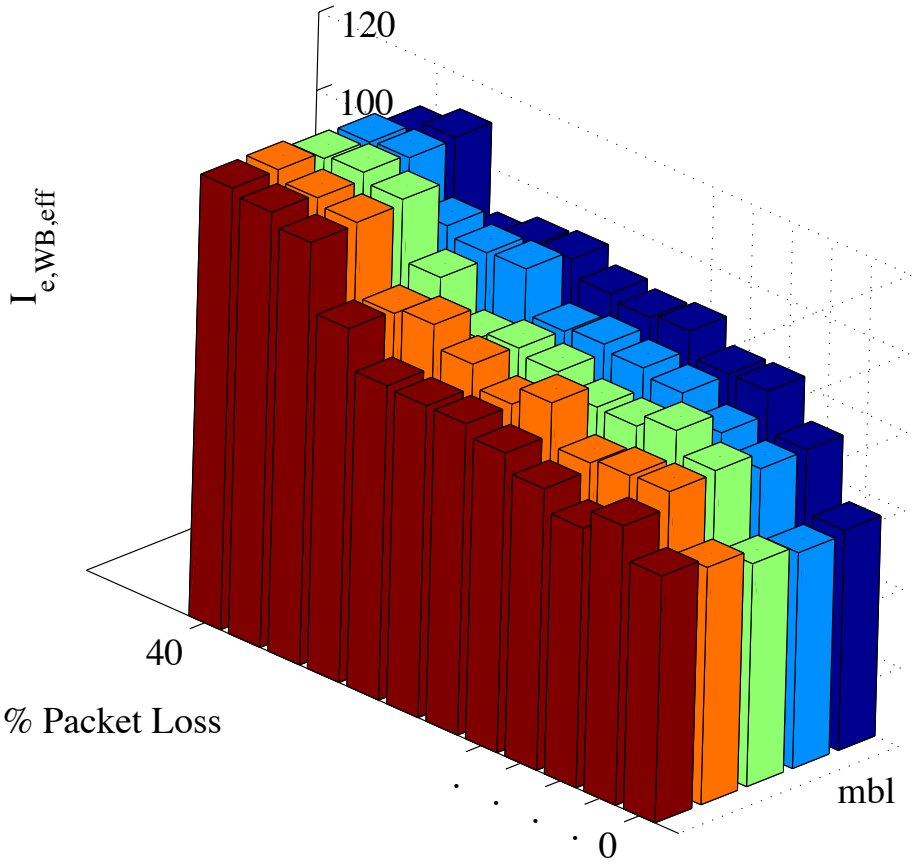


Figure 6.8: Variation of $I_{e,WB,eff}$ against mlr (%) and $mbl = [1, \cdots, 5]$ for AMR-WB 23.85 kbps, PI=1.

$$I_{e,WB,eff} = I_{e,WB} + (129 - I_{e,WB}) \times \frac{P_{pl}}{P_{pl} + Bpl} \tag{6.5.5}$$

The equation is similar to equation (6.3.1) differing in the constant term, 95, which is replaced with the new R_{max}=129. The $BurstR$ parameter is also absent here. Bpl values for this equation were computed separately for each of the codecs over the training data, and the performance was analysed using the testing data. Loss distributions were assumed to be random, which may be thought to be a reasonable

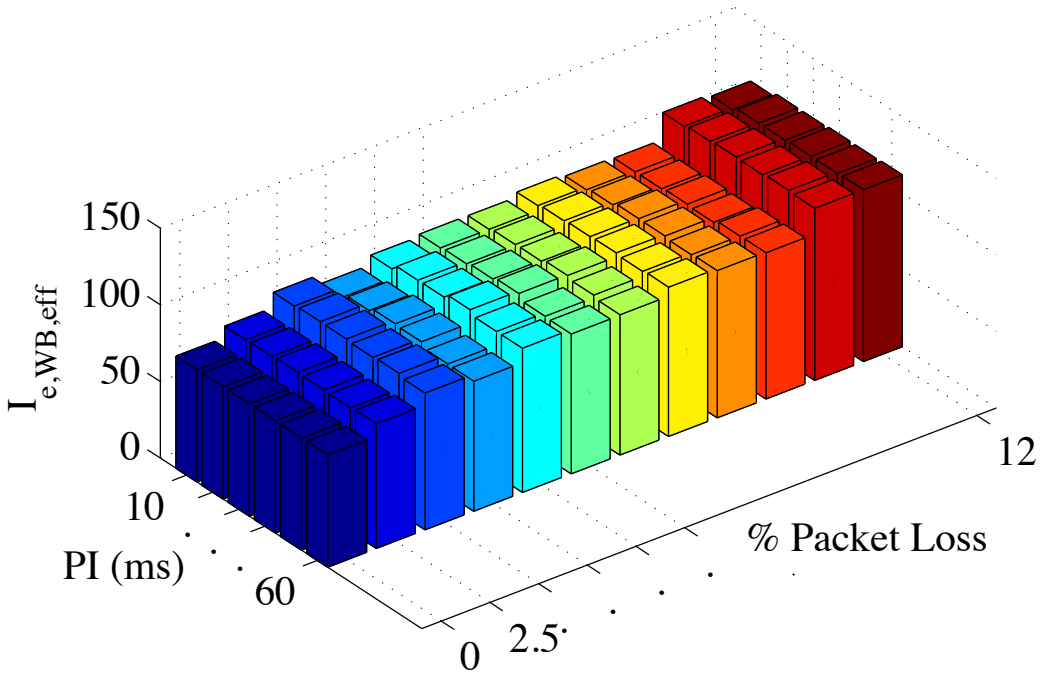


Figure 6.9: Variation of $I_{e,WB,eff}$ against mlr (%) and $PI = [10, \cdots, 60ms]$ for G.729

assumption since it was shown in Figures 6.8 and 6.9 that WB-PESQ estimates are oblivious of the effect of burstiness and varying PIs. The results are reported in Table 6.4 for each codec. The table also shows the RMSE of equation (6.5.3) for AMR-NB (7.4 kbps) and G.722.1 (32 kbps). These codecs were not represented in the training data during evolution. Percentage *Prediction Gain (PG)* of 16.36 % was observed for unseen data in an RMSE sense. This is calculated according to equation (6.5.6)

$$\%PG = \frac{RMSE_e - RMSE_p}{RMSE_e} \times 100 \tag{6.5.6}$$

where, $RMSE_e$ and $RMSE_p$ represent the $RMSE$ of equations (6.5.5) and (6.5.3) respectively.

However, equation (6.5.5) (i.e. the E-model formulation) does not account for bursty packet losses and also for PI spanning multiple speech frames. Moreover, all the models proposed in this research (by equations (6.5.2)–(6.5.4)) are functions of mbl. Given this, a comparison between E-model and the proposed models over datasets that include various degrees of burstiness and PIs is somewhat unfair. To ensure fairness a different simulation study was performed in which speech files were subjected to random packet losses with loss rates ranging between [0,2.5,. . . , 15, 20, . . . , 40]% for each of the encoding conditions. The results are reported in Table 6.5. To this end, the data was split into training and testing datasets as previously. Bpl values were recalculated for each of the codecs and the RMSE was noted with respect to WB-PESQ. The performance of equation (6.5.3) was found to be inferior to the traditional E-model formulation initially. Since random loss conditions were alien to the GP training conditions, the performance degradation was not unexpected when compared to a retuned E-model. However, upon merely re-scaling equation (6.5.3) using training data a prediction gain of approximately 36% was obtained. This shows the robustness of the model produced by GP as evolutionary re-training was not required. Linear re-scaling resulted in new *slope* and *intercept* terms which were found to be 0.5085 and 46.7468 respectively. Linear re-scaling was done by treating equation (6.5.3) with equations (4.3.2) and (4.3.3). A pictorial comparison similar to Figure 6.6 is also done between equations (6.5.3) and (6.5.5) with respect to WB-PESQ in Figure 6.10 for the case of ITU-T G.723.1 codec. It can be observed that the points produced by equation (6.5.3) are more firmly glued to the 45% reference line as compared to those produced by equation (6.5.5).

Table 6.4: Comparison between the Prediction Accuracies of the E-Model and the Proposed Model

Codec (kbps)	**E-Model**			**Equation (6.5.3)**	
	Bpl	RMSE train	RMSE test	RMSE train	RMSE test
G.722.1 (24)	20.32	8.6824	8.8958	8.1701	8.9118
G.722.2 (6.6)	40.75	9.6225	8.9933	8.0938	7.6603
G.722.2 (8.85)	28.74	10.0175	9.9919	8.0185	7.8304
G.722.2 (12.65)	21.58	10.5538	10.4088	8.2188	8.0678
G.722.2 (14.25)	21.03	10.4684	11.2854	8.3031	8.5836
G.722.2 (15.85)	19.98	10.599	11.5020	8.3257	9.1166
G.722.2 (18.25)	19.48	11.2017	10.92	8.6862	9.0266
G.722.2 (19.85)	18.86	10.5502	11.3529	8.2338	8.7685
G.722.2 (23.05)	18.44	11.4079	11.1663	9.1417	8.7729
G.722.2 (23.85)	17.92	10.789	11.1948	8.6125	9.3168
G.729 (8)	28.43	8.95	9.1631	7.3888	7.4943
G.723.1 (6.3)	29.19	10.83	10.3630	8.8116	8.5259
AMR-NB (12.2)	13.50	8.0689	7.2947	9.4549	8.7322
G.722.1 (32)	18.93	8.9112	–	–	8.4775
AMR-NB (7.4)	15.71	7.1335	–	–	8.6188
Average	–	9.8527	10.1946	8.42	8.5269
% PG	–	–	–	14.54	16.36

6.6 Conclusions

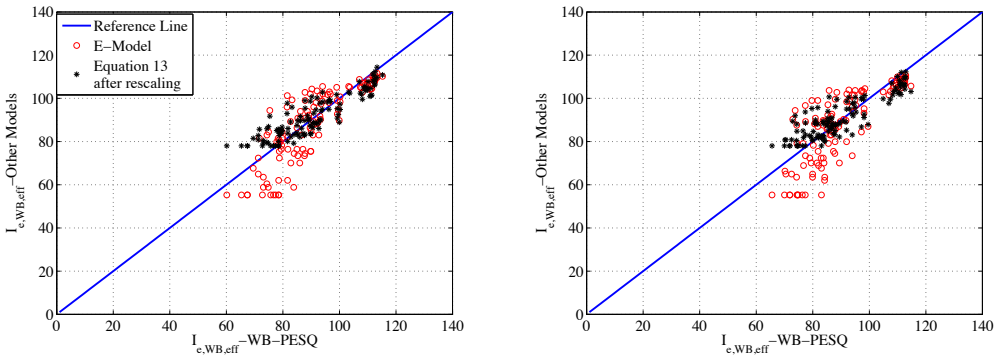
In this Chapter we have proposed a novel methodology for determining NB/WB equipment impairment factors, $I_{e,WB,eff}$, for a mixed NB/WB context. It is based on using GP to perform symbolic regressions which generate simple formulae for $I_{e,WB,eff}$. It is advantageous in the sense that the derived models do not result from human bias, but as a direct consequence of program evolution. Moreover, parameter optimization is done in parallel with evolution for every model using linear scaling. The derived models are applicable for the network distortion conditions under observation. Our approach utilizes WB-PESQ for deriving reference values of $I_{e,WB,eff}$ as opposed to subjective tests. This is suitable for fast and inexpensive derivation of

Table 6.5: Comparison between the Prediction Accuracies of the E-Model and the Proposed Model for Random Loss Conditions

	E-Model			**Equation (6.5.3)**		**Equation (6.5.3) After Rescaling**	
Codec (kbps)	Bpl	RMSE train	RMSE test	RMSE train	RMSE test	RMSE train	RMSE test
G.722.1 (24)	11.97	12.2622	13.1168	14.9678	14.8504	6.6551	6.9227
G.722.2 (6.6)	24.06	8.5488	8.5060	8.2690	7.8553	6.9593	7.2537
G.722.2 (8.85)	14.61	9.7573	9.8179	11.2923	11.3162	5.9292	6.2118
G.722.2 (12.65)	10.62	11.2011	11.2734	14.4629	14.7035	6.6388	6.7783
G.722.2 (14.25)	10.01	11.2489	11.1616	15.0003	14.8100	6.2532	6.5631
G.722.2 (15.85)	9.90	11.7606	12.1703	15.5678	15.6983	6.4557	6.9346
G.722.2 (18.25)	9.36	12.3315	12.7594	16.5918	17.0715	6.9336	7.3102
G.722.2 (19.85)	9.06	12.3594	12.1367	16.8570	16.8927	6.9994	6.9165
G.722.2 (23.05)	8.37	13.1165	12.9824	18.1885	17.9847	7.1816	7.3181
G.722.2 (23.85)	8.52	12.6131	12.4198	17.7068	17.3806	7.0750	6.6818
G.729 (8)	16.82	8.5228	8.7014	9.6080	9.7882	5.5697	5.5535
G.723.1 (6.3)	14.95	9.5020	10.3181	10.7527	11.1905	6.4791	6.6315
AMR-NB (12.2)	5.76	8.6698	8.3887	17.9201	18.4502	9.2798	9.6566
G.722.1 (32)	11.69	14.0378	13.6078	16.3347	15.7470	7.4048	7.8482
AMR-NB (7.4)	7.59	7.8755	8.5562	14.7356	14.7646	7.8499	7.7822
Average	–	10.9205	11.0611	14.5504	14.5669	6.9109	7.0909
% PG	–	–	–	-33.2393	-31.6949	36.7163	35.8934

reference $I_{e,WB,eff}$. We have demonstrated the utility of our approach by generating three models for $I_{e,WB,eff}$ from different GP runs. The proposed models were thoroughly tested on a wide variety of VoIP traffic scenarios including a blend of modern IP telephony codecs.

A comparison of equation (6.5.3), which has the best performance among the proposed models, with the E-Model, equation (6.5.5), has also been done, where it is shown that our approach outperforms the E-Model with a significant margin in terms of prediction accuracy. Even though we have used WB-PESQ in this research, the proposed methodology is independent of it and simply requires a generic instrumental model of this kind. The methodology may also be augmented with subjective tests.



(a) (b)

Figure 6.10: $I_{e,WB,eff}$ predicted by equation(6.5.5) (i.e. the E-Model) and equation (6.5.3) vs target $I_{e,WB,eff}$ obtained from WB-PESQ for random loss: (a) training data (b) testing data.

Chapter 7

Real-Time, Non-Intrusive Speech Quality Estimation: A Signal-based Model

7.1 Introduction

Chapters 5 and 6 introduced parametric models for speech quality estimation. Sometimes, however, it becomes incumbent to employ a signal-based model to estimate speech quality. Firstly, signal-based models are applicable to a wider variety of networks than parametric ones[1]. Moreover, in the case of VoIP, there are certain types of network distortions whose impact on speech quality cannot be measured using parametric models. For instance, during transmission over WLANs speech frames may undergo bit-errors whose effect on perceptual quality may not be measurable using a parametric model. Similarly, the asymmetry of distortions in the case of transcoding was discussed in Section 2.4.5. Quality degradation while the speech signal traverses multiple codecs in a given order may not necessarily be the same for a different order. It is due to such reasons that parametric models may give false predictions on speech

[1]Since parametric models are designed for a particular type of communications network, their predictions for that type of network are more accurate than those of signal-based models; signal-based models are suitable for general predictions for a wider variety of networks.

quality. Signal-based models may be more useful in such scenarios.

Signal-based models are used to analyze speech quality when the spectral envelope of the speech signal may have suffered from degradation. Considerable work has been done in the past on devising signal-based models. An example of such a model is the current, state-of-the-art, ITU-T Recommendation P.563 for *single-ended* estimation of speech quality [ITU-T, 2005d].

In this chapter we propose a new non-intrusive signal-based model for speech quality estimation in a narrowband (NB) context. In particular we have employed a hybrid optimization approach that uses Genetic Programming (GP) to search for a suitable structure for the desired solution. Coefficients of the models evolved by GP are tuned simultaneously using a Genetic Algorithm (GA) and *linear scaling*. The use of hybrid optimization is novel here when compared to chapters 5 and 6.

The rest of this Chapter is organized as follows. Section 7.2 discusses the nature of signal based models. Section 7.3 discusses the various experimental details and test results. Finally section 7.4 presents the conclusion.

7.2 Signal Based Non-Intrusive Models

Unlike parametric models, signal-based models process the audio stream to extract the information relevant to distortions in a signal. The estimated distortions are then converted into *MOS* estimates for that audio stream. Given this, a signal based model may have two main modules. 1) A feature extractor that processes the speech signal and extracts cogent distortion indicators. To this aim, various speech processing algorithms have been devised for feature extraction. 2) A mapping module that transforms the extracted features into MOS estimates. In what follows, some of the well known algorithms that have been used in the past for both feature extraction and MOS mapping are briefly described.

7.2.1 Feature Extraction Algorithms

Feature extraction algorithms may involve time and/or frequency domain analysis of the speech signal under test. Time domain analysis may involve computation of distortions relevant to the waveform of the speech signal. Some distortions of this type include temporal clipping, level variation and abrupt changes in the temporal envelope of the signal.

Frequency domain analysis techniques normally emulate the human vocal production system [Gray et al., 2000], or the auditory processing system of the human ear. Perceptual Linear Prediction (PLP) [Hermansky, 1990] is one of the exemplary algorithms for speech processing and feature extraction. It was first employed by [Liang and Kubichek, 1994] Liang and Kubichek in 1994 for non-intrusive speech quality estimation. It was originally developed for speaker independent automatic speech recognition and is an emulation of the human auditory system.

ITU-T Recommendation P.563 [ITU-T, 2005d] is the current standard for signal-based non-intrusive speech quality estimation. It entails a rigorous feature extraction process that involves the computation of plausible features from both time and frequency domain representations of the signal under test. The algorithm has been discussed in section 3.3.3.

7.2.2 Mapping Algorithms

Once cogent features corresponding to the speech signal under test have been extracted, they are mapped to the speech quality using an appropriate regression or classification tool or a machine learning algorithm. Thus, for training a model numerous MOS-labelled speech databases are used. An MOS-labelled speech database may have a considerable number of speech samples from both male and female speakers, and possibly in different languages. The duration of each speech sample may vary

from 8-12 secs. Each speech sample may be affected by a certain type of network distortion, such as frame erasure, bit errors and/or signal correlated/uncorrelated noise. Each sample also has a MOS score associated with it, derived normally from subjective tests [ITU-T, 1996c]. The features relevant to distortions for all the samples serve as the input domain variables and the corresponding MOS scores form the target values for learning. After learning completes, the derived model is also tested and validated using unseen data from a separate set of speech samples/databases, as a standard practice.

Numerous learning algorithms have been used in the past to map the effect of speech features, and/or their relevant statistics, to speech quality. Depending upon the learning algorithm the training and mapping procedures may vary. One approach is to compute a significant number of feature vectors corresponding to clean, distortion free, speech files. A database of clean speech feature vectors may be formed by classifying the latter into clusters to form a reference code-book. An appropriate vector quantization algorithm such as K-means, as in [Jin and Kubichek, 1996], or self organizing maps, as in [Picovici and Mahdi, 2004], may be employed. As a part of training, feature vectors corresponding to distorted speech samples are extracted and their distances are computed from the best matching feature vector in the reference code-book in a Euclidean sense. These auditory distances are eventually mapped to reference MOS scores using a 2^{nd} or a 3^{rd} order polynomial. An obvious limitation of such an approach is the time required to search for a best matching vector from the reference code-book of feature vectors of clean speech. Another approach is to map the feature vectors of the training speech samples directly to speech quality using an artificial neural network [Tarraf and Meyers, 1999]. In [Falk and Chan, 2006] Falk and Chan have used Gaussian mixture models (GMMs), support vector classifiers and multi adaptive regression splines at various stages of their proposed algorithm to map the cogent features to speech quality. Similarly in [Grancharov et al.,

2006] Grancharov et al. also employed a GMM for speech quality prediction. In [Li and Kubichek, 2003] Li and Kubichek employed a hidden Markov model (HMM) for mapping the speech related features to quality. Among all of these algorithms HMMs attempt to explore statistical dependencies between adjacent segments of human speech, whereas for the rest of the algorithms aggregated values of features over the entire length of a speech signal are used.

ITU-T performs perceptual mapping between the features of speech signal under test and the speech quality. The mapping process has already been discussed in section 3.3.3.

7.2.3 The Proposed Model

This chapter proposes a new model for speech quality estimation. We have used P.563 as the feature extraction algorithm in this research. This has been chosen for two reasons: 1) P.563 is the current, state-of-the-art standard for non-intrusive speech quality estimation. 2) it computes the most numerous and most varied features relevant to speech quality than any other feature extraction algorithm. However, for mapping the features to speech quality we have employed a GP based symbolic regression approach, along with a traditional GA, and linear scaling as proposed by Keijzer in [Keijzer, 2004], for parameter optimization. GP is used to evolve a suitable structure for mapping the features to speech quality. As described in Chapter 4 GP is also known to prune off the redundant features and to retain the most useful ones in the genome of the final individual. The GA is employed to fine tune the numeric leaf values during evolution.

7.3 Experiments and Results

7.3.1 Experimental Setup

As a first step feature extraction was performed by processing various MOS labeled speech databases using the P.563 algorithm. A total of eight subjectively evaluated speech databases were used in this research. Out of these, seven *multilingual* databases belong to the ITU-T P-series supplement 23 (Experiments 1 and 3) [ITU-T, 1998a]. These databases include 1328 speech samples distorted due to conditions such as *signal correlated noise, transcoding, bit errors* and *frame erasures*. The databases include utterances by male and female speakers. The eighth database includes 240 utterances in the North American English accent by two male and two female speakers with seven types of distortion conditions. This database is compiled by Nortel Networks [Thorpe and Yang, 1996]. The distortion conditions, each of varying levels, include *signal correlated noise, coding distortions, tandeming, temporal clipping, bit errors* and *speech level variation*. 70% of the speech files, and their corresponding MOS, in these databases were dedicated for training and the remaining 30% for testing reasons. More specifically, input/output patterns of 1,100 speech files were picked randomly as training data, and the remaining, 468 patterns were used for the purpose of testing.

Values of 43 features corresponding to each of the speech files were accumulated as the input domain variables. The corresponding MOS scores formed the target values for training and testing the evolutionary experiments.

Three GP experiments were conducted. The common parameters of these experiments are listed in Table 7.1. In all of these population size was set to 3,000. Each experiment was composed of 50 runs, each spanning 100 generations. Tournament selection with lexicographic parsimony pressure (LPP) was used in both experiments [Luke and Panait, 2002]. An initial maximum tree depth of 6 was used. The

maximum tree depth was changed dynamically with an upper limit of 17. Survival was based on elitism. The elitist criterion was such that at each generation the depth of the best individual would be noted. Any individuals in the child population exceeding this depth would be removed from evolution at this stage as a first step. Next, up to half of the entries of the new population would be filled up with the remaining individuals from the offspring population on the basis of fitness. The remaining slots in the new population would be filled with the fittest individuals from the parent population.

Table 7.1: Common Parameters of GP experiments

Parameter	**Value**
Population Size	3,000
Initial Tree Depth	6
Selection	LPP Tournament
Tournament Size	7
Genetic Operators	Crossover, Subtree Mutation and Point Mutation
Operator Probabilities	0.95, 0.1, 0.1
Survival	Elitist
Function Set	+, -, *, /, sin, cos, log_{10}, log_e, sqrt, power.
Terminal Set	Random numbers [-6–6]. P.563 features.

In all of the experiments scaled mean squared error (MSE_s) was used as the fitness criterion and is given by equation (4.3.2).

Instead of using *protected* functions, any inputs were admissible to all the functions. For the input values outside the domain of the functions *log, sqrt, division* and *pow*, NaN (undefined) values were generated. This results in the individual concerned being assigned the worst possible fitness.

The selection criterion was based on the notion that population diversity can be enhanced if mating takes place between two, fitness-wise, dissimilar individuals, as suggested by Gustafson et. al. [Gustafson et al., 2005].

The first experiment (referred to as experiment 1) was based purely on GP i.e.,

without hybrid optimization. In the second experiment (referred to as experiment 2) the leaf coefficients of the GP trees were tuned using a GA during evolution. This embodies hybrid optimization. A problem associated with such an approach is that the overall optimization algorithm becomes fairly compute-intensive. Thus, to strike a balance between fitness enhancement and computational efficiency, we chose to fine-tune the leaf coefficients of the 30 best trees only of any given generation during evolutionary runs. This amounts to 1% of the total trees being subjected to parameter tuning. The coefficients learnt by the GA based tuning were coded back in to the respective GP trees. It was hoped that this would enhance the overall fitness of the subsequent populations as the genetic material of these possibly more fit GP trees would propagate to the subsequent generations. Here, a simple GA was implemented with genes of type *double*. A population of size 100 was used with 15 generations per run. Single point crossover and mutation were used as the the genetic operators with probabilities equal to 0.8 and 0.2 respectively.

The last experiment (referred to as experiment 3) was similar to experiment 1. However, here the tree-coefficients of all the individuals of final generations of all the runs were tuned using GA. This is also aimed at computational efficiency whereas it was also hoped that coefficient tuning would result in improved fitness. The number of generations of each run of the GA were changed to 50.

7.3.2 Results and Analysis

Table 7.2(a) lists the statistics about the MSE_s of the training/testing data and final tree size (in terms of number of nodes) of the best individuals of the two experiments under consideration. The fitness statistics relevant to experiment 2 are generally better as compared to experiments 1 and 3 over both training and testing data. Nonetheless, a Mann-Whitney-Wilcoxon test was also performed to formally decide

if a significant difference exists between the experiments at a 5% significance level. The results are shown in Table 7.2(b) where a value of '0' means that a significant difference does not exist between two experiments, a value of '1' means the converse, and an 'x' states that same experiments are not to be compared. The significance test did not reveal any difference between experiments 1 & 2, and consequently between the two approaches. Experiment 3 was significantly different from experiment 1 in terms of fitness over test data, however a similar difference between experiments 3 and 2 could not be ascertained. However, the best individual, in terms of minimum MSE_s over the testing data, belongs to experiment 2, as can be seen in Table 7.2(a).

Table 7.2: Statistical analysis of the GP experiments

(a) MSE Statistics for Best Individuals of 50 Runs for the three Experiments

	Experiment 1			**Experiment 2**			**Experiment 3**		
Stats	MSE_{tr}	MSE_{te}	$Size$	MSE_{tr}	MSE_{te}	$Size$	MSE_{tr}	MSE_{te}	$Size$
Mean	0.3673	0.3488	35.58	0.3618	0.3441	36.16	0.3619	0.3391	0.952
Std. Dev.	0.0172	0.0183	13.9972	0.0159	0.0169	17.5875	0.0192	0.0173	2.6972
Max.	0.4049	0.4026	70	0.3885	0.3817	102	0.4137	0.3841	17
Min.	0.3239	0.3146	12	0.3271	0.3071	18	0.3125	0.3104	5

(b) Results of Mann-Whitney-Wilcoxon Significance Test

	Experiment 1			**Experiment 2**			**Experiment 3**		
	MSE_{tr}	MSE_{te}	$Size$	MSE_{tr}	MSE_{te}	$Size$	MSE_{tr}	MSE_{te}	$Size$
Experiment 1	x	x	x	0	0	0	0	1	0
Experiment 2	0	0	0	x	x	x	0	0	0
Experiment 3	0	1	0	0	0	0	x	x	x

Figure 7.1 compares the three experiments from a different vantage point. The means and variations of fitness values of best individuals, over training data, at a given generation over all the runs are plotted for each experiment. Firstly, it can be seen that up to almost the first 40 generations the fitness statistics of the three experiments do not vary from each other. For the subsequent generations the fitness curve for experiment 1 is different from those of the other experiments. However, experiment 3 has a similar curve to that of experiment 2. It is worth mentioning that

the configuration of experiment 3 is similar to that of experiment 1 except for its last generation where its tree-coefficients were tuned using a GA. Thus a difference between the three experiments cannot be ascertained from these observations too. Moreover, the curves in Figure 7.1 also suggest that maximum enhancement in fitness (i.e., reduction in MSE_s) occurs within the first 40 generations. The gain beyond this point is gradual, owing possibly to the *stagnation* of subsequent populations.

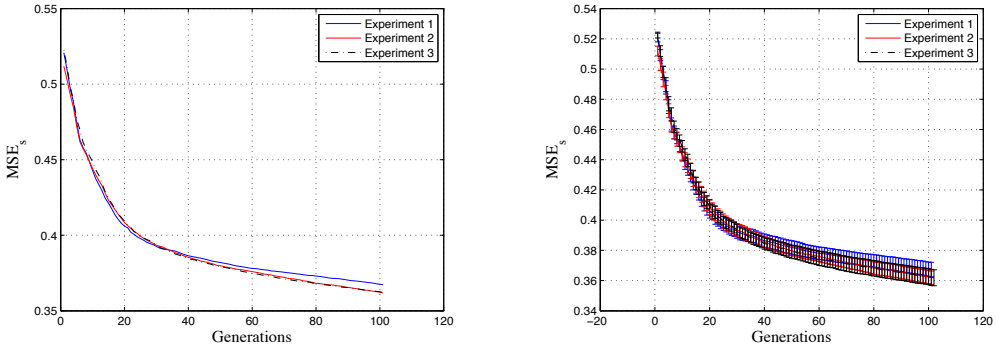


Figure 7.1: Statistics of fitness over training data for the best individuals across various runs of the three experiments as a function of generation-number. (a) shows averages (b) shows error-bars corresponding to 95% confidence interval

Performance results of the best individual over the testing data are shown in Table 7.3 and a comparison with the reference implementation of ITU-T P.563 is also shown. Table 7.3 also lists the percentage of Prediction Gain (PG) given by equation (7.3.1). This individual is the proposed model and is derived from experiment 2.

$$\%PG = \frac{MSE_{P.563} - MSE_p}{MSE_{P.563}} \times 100 \tag{7.3.1}$$

where $MSE_{P.563}$ and MSE_p represent the MSE of ITU-T P.563 and the proposed model with respect to reference MOS respectively.

The proposed model has 85 nodes (including terminals and functions), however,

Table 7.3: Performance results of the proposed model versus the reference implementation of ITU-T P.563 in terms of MSE_s

	ITU-T P.563	GP Based Model	Percentage Enhancement
Training	0.3937	0.3415	9.89
Testing	0.3674	0.3071	16.41

it is a function of only *9* features as opposed to *43* features of the reference implementation of ITU-T P.563. This may prove beneficial in reducing the computational requirements of the algorithm. The model is presented in appendix B. The independent variables (i.e. features of P.563) are briefly discussed as follows:

- *Average pitch:* This feature is used as a basic speech descriptor. An autocorrelation method is used to compute pitch period estimates of 64 ms *voiced* frames. Average pitch is one of the distortion classifiers and is used mainly to differentiate between unnatural male and female voices. It is also used by ITU-T P.563 to formulate the initial estimate of quality.

- *Final VTP average:* VTP refers to an array that stores the cross sectional areas of the emulated vocal tract tubes, as described in the first principle of ITU-T P.563 in section 7.2.1. Final VTP average relates to the mean of the area of last tube over the entire length of the signal.

- *ART average:* ART (articulators) are formed by aggregating the elements of the VTP elements into three groups. These groups correspond to the front, middle and rear *cavities* of the human vocal tract. This feature represents the average size of the rear cavity.

- *Basic voice quality:* This feature is derived from the second principle of ITU-T P.563 described in section 7.2.1.

- *LPC kurtosis, LPC skewness and absolute LPC skewness:* These three features

represent statistics relevant to the 21 (LPC) *linear predictive coefficients* of the speech signal. The statistics are computed for the LPCs of each frame and aggregated over all frames of the signal. Skewness and kurtosis are the 3^{rd} and 4^{th} moments about the mean and are considered to give meaningful insights into the spectral characteristics of the signal.

- *Spectral clarity:* This feature is computed for voiced sections of the speech signal to be analyzed. It corresponds to the difference between the values of harmonics of pitch and the non-harmonic spectral components in the gaps between the harmonics. First five harmonics of the pitch are used. FFT is used for spectral estimation.

- *Estimated segmental SNR:* This feature is used to detect the presence of signal correlated noise.

7.4 Conclusion

In this chapter we have proposed a novel method to derive superior signal-based non-intrusive speech quality estimation models. ITU-T P.563 algorithm was used for feature extraction in this research. Three GP experiments were conducted to find a viable model. One of the experiments was based solely on the use of GP for model development, whereas in the subsequent experiments a GA was employed to tune the leaf-coefficients of the GP trees. The latter two experiments represent hybrid optimization approaches. The outcome of the research is a new model for deriving a speech quality estimation model that outperforms the reference implementation of ITU-T P.563. The derived model is a function of only 9 features whereas the reference implementation of P.563 uses 43 features. This may potentially lead to a computationally more efficient algorithm. Although, the P.563 algorithm has been

used in this research for feature extraction, our approach is more general and can be used in conjunction with other speech processing algorithms or auditory models.

Chapter 8

Conclusions and Future Work

8.1 Conclusions

The aim of this thesis was to derive effective non-intrusive speech quality estimation models. Effectiveness was desired in two senses. Firstly, it was sought to derive models with better prediction accuracy as compared with contemporary models. Secondly, it was expected that the derived models have better computational efficiency. To achieve these objectives *genetic programming* based symbolic regression has been employed. Equal emphasis has been paid on deriving parametric and signal-based models. To these ends, disparate models are presented in chapters 5, 6 and 7 that solve different problems.

Chapter 5 presents parametric models to estimate speech quality of VoIP in a narrowband (NB) context. A number of modern NB codecs were employed in this research. ITU-T P.862 [ITU-T, 2001b] (the PESQ algorithm) was used as a reference model. The chapter also performs parameter significance analysis by examining the composition of *genomes* of the best individuals of evolutionary runs. A descriptive comparison of the derived models with contemporary models is performed where

strengths of the proposed models are highlighted.

Chapter 6 takes a step further by deriving effective equipment factors for ITU-T G.107 [ITU-T, 2005a] (the E-Model) in a mixed narrowband/wideband (NB/WB) context where packet loss and codec related impairments due to NB and WB codecs may be present. A number of modern NB and WB codecs recommended by ITU-T were chosen. The derived impairment factors outperform the E-Model for equipment impairment factors in terms of prediction accuracy. Apart from deriving equipment impairment factors using GP, an additional advantage of the research was that it used WB-PESQ [ITU-T, 2005f] for obtaining reference/target values for training. The methodology presented is, however, generic, and may replace WB-PESQ with any instrumental model. The advantage of using instrumental models such as WB-PESQ is that the results can be derived quickly.

The focus of chapter 7 was on derivation of signal-based models for speech quality estimation. To this aim ITU-T P.563 [ITU-T, 2005d] was used as a feature extraction algorithm. A hybrid optimization approach was employed in which GP was used to find an appropriate structure of the target model, where a genetic algorithm (GA) was employed to tune the leaf coefficients of GP trees during evolution. Various experiments were performed and the aim was to derive a better model for mapping the features of ITU-T P.563 on to speech quality. Thus, a nonlinear model was found that outperformed the linear mapping function of the reference implementation of ITU-T P.563. The resulting model also had a reduced dimensionality as it was a function only of 9 features of the ITU-T P.563 algorithm as opposed to the 43 features of the reference implementation of the algorithm. This may be useful in enhancing the computational efficiency of the algorithm.

The results of this thesis further consolidate the notion of GP being a strong machine learning algorithm. Of special interest is the algorithm's ability to solve a user defined problem with minimal user intervention. As compared to other approaches

where the practitioner has to deal with worries of manual curve fitting or finding an appropriate model structure for target data, GP performs these tasks automatically once provided with the data of the problem domain. In addition it also lends itself to easy integration with other numerical coefficient optimization algorithms. An application of this has also been demonstrated in chapter 7.

8.2 Future Work

A plethora of future goals and research problems may be defined in the light of this thesis. These are discussed as follows:

1. It must be emphasized that the focus of this research was to derive quality estimation models for *listening only* scenarios. A future objective would be to derive a model for *conversational* quality estimation of a call. Conversational quality suffers due to increase in the end-to-end delay. A next objective may be to estimate the combined effect of VoIP traffic parameters including the end-to-end delay on call quality.

2. In chapter 7 a signal-based model was proposed for speech quality estimation. An immediate future objective could be to test the model on a wider variety of network distortion conditions. An additional future objective is to benchmark the computational performance of the proposed model.

3. Current signal-based non-intrusive models are designed for NB telephony. A major trend in non-intrusive estimation of speech quality is towards WB signals. Chapter 6 was dedicated to derivation of equipment impairment factors for E-Model in a mixed NB/WB context. As a followup of that a future research goal may be to develop a signal-based model for a mixed NB/WB context.

4. Development of a hybrid non-intrusive model that is a function of cogent transport layer metrics as well as of significant features of the speech signal under test. This is aimed at achieving a higher prediction accuracy by circumventing the weaknesses of both types of models.

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Appendix A

Transformation Between MOS and R

This appendix presents the equations to transform MOS to R and vice versa. R can be converted to MOS using equation (A.0.1).

$$MOS = \begin{cases} 1 & \text{for } R \leq 0 \\ 1 + 0.035R + R(R-60) & \\ \times(100-R)7 \times 10^{6}, & \text{for } 0 < R < 100 \\ 4.5 & \text{for } R \geq 100 \end{cases} \tag{A.0.1}$$

Similarly, Hoene et al. in [Hoene et al., 2004] proposed an inversion of equation (A.0.1) which is now a part of the E-Model (see Appendix I in [ITU-T, 2005a]). In the range 6.5≤ R≤ 100, R can be calculated from MOS using the formula:

$$R = \frac{20}{3}\left(8 - \sqrt{226}cos\left(h + \frac{\pi}{3}\right)\right) \tag{A.0.2}$$

with:

$$h = \frac{1}{3}arctan2\left(18566 - 6750MOS, 15\sqrt{-903522 + 1113960MOS - 202500MOS^2}\right) \tag{A.0.3}$$

and:

$$arctan2(x,y) = \begin{cases} arctan\left(\frac{y}{x}\right) & \text{for } x \geq 0 \\ \pi - arctan\left(\frac{y}{-x}\right) & \text{for } x < 0 \end{cases} \tag{A.0.4}$$

Appendix B

Signal-based Model

This appendix presents the signal-based non-intrusive model resulting from the research presented in chapter 7. The model is presented using tree representation. The interpretation of the functions and terminals is as follows:

+: Add

-: Subtract

*: Multiplication

/: Division

ln: Natural logarithm

x1: Average pitch

x2: Final VTP average

x3: ART average

x4: Basic voice quality

x5: LPC kurtosis

x6: LPC skewness

x7: Absolute LPC skewness

x8: Spectral clarity

x9: Estimated segmental SNR

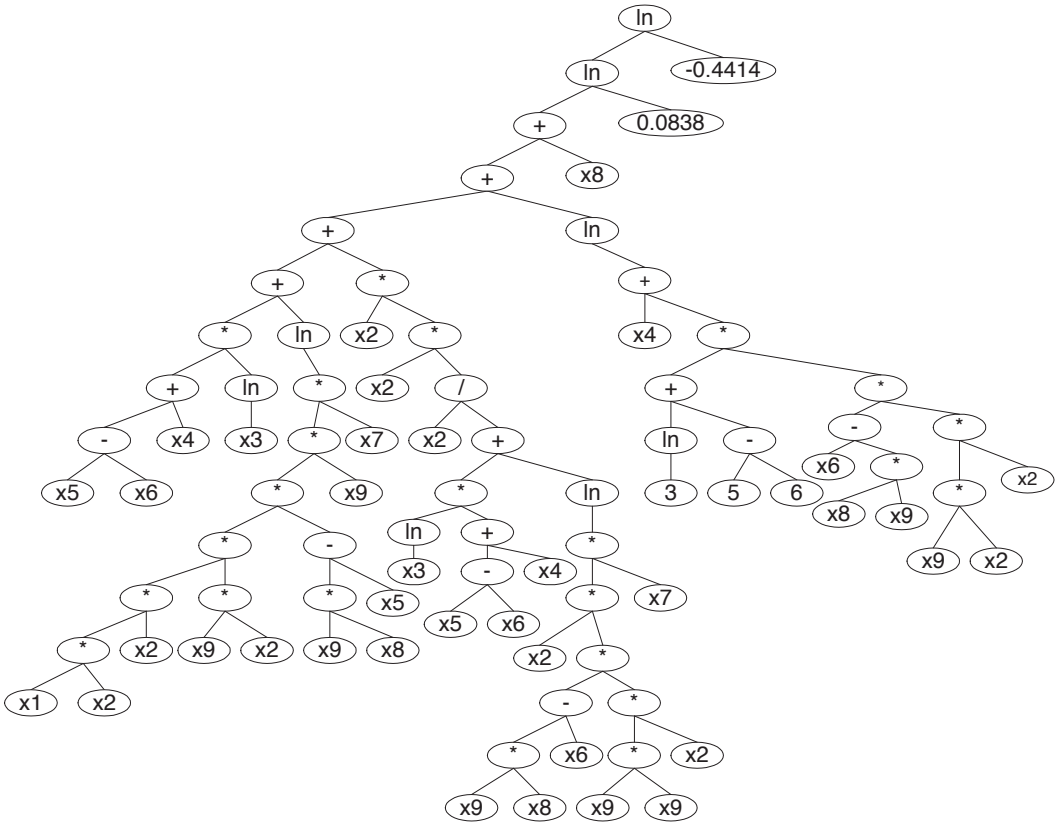

Figure B.1: Signal-based model resulting from the research presented in chapter 7

Appendix C

List of Publications

Journal

- Adil Raja, R. Muhammad Atif Azad, Colin Flanagan and Conor Ryan *A Methodology for Deriving VoIP Equipment Impairment Factors for a mixed NB/WB Context*, to be Published in IEEE Transactions on Multimedia.

- Adil Raja, R. Muhammad Atif Azad, Colin Flanagan and Conor Ryan *Evolutionary Speech Quality Estimation in VoIP*, to be Published in Soft Computing Journal, Sprindger.

Conference

- Adil Raja, R. Muhammad Atif Azad, Colin Flanagan and Conor Ryan *VoIP Speech Quality Estimation in a Mixed Context with Genetic Programming*, In Proceedings of Genetic and Evolutionary Computation Conference, July 2008.

- Adil Raja and Colin Flanagan *Real-Time, Non-Intrusive Speech Quality Estimation: A Signal-based Model*, In Proceedings of 11^th European Conference on Genetic Programming (EuroGP), March 2008.

- Adil Raja, R. Muhammad Atif Azad, Colin Flanagan and Conor Ryan *'Real-Time, Non-Intrusive Evaluation of VoIP'*, In Proceedings of 10^{th} European Conference on Genetic Programming (EuroGP), 2007. *Nominated for best paper award*

- Adil Raja, R. Muhammad Atif Azad, Colin Flanagan, Dorel Picovici and Conor Ryan *'Non-Intrusive Quality Evaluation of VoIP Using Genetic Programming'*, In the proceedings of First International Conference on Bio Inspiered Models of Networks Information and Computer Systems (Bionetics), 2006, Cavalese, Italy.

- Dorel Picovici, Adil Raja, and Colin Flanagan, *'Real-time Non-intrusive VoIP Evaluation Using Second Generation Network Processor'*, IEEE International Conference on Acoustics Speech and Signal Processing, 21-24 May 2006, 1208-1211.