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Masters of Engineering

VOWEL CODING USING AN ARTICULATORY MODEL

By

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Submitted to

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The research contained herein was completed by me, the undersigned.

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Date: 22/9/88.

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ABSTRACT

An investigation into articulatory vocoding for vowels, as a means of achieving high quality coding at low bit rates, is carried out in this thesis. Methods of estimating the vocal tract transfer function from the speech wave are compared, and an algorithm for closed glottis interval (CGI) analysis is developed. CGI analysis is chosen over autocorrelation based inverse filtering methods.

Various distortion measures for use in Vector Quantization are evaluated, and a new covariance distortion measure is proposed. It is shown that this measure yields close matches from an acoustic codebook.

An articulatory coding system is designed, including a linked codebook of articulatory shapes, based on synthetic speech. A method of generating a similar codebook from real speech is proposed, and an investigation into estimating articulatory parameters from the speech wave is carried out to this end.

ACKNOWLEDGEMENTS

Much thanks to my supervisor, Dr. Sean Marlow, for his advice and encouragement during the last two years. I would also like to thank Dr. Ronan Scaife of UCG for providing the ASY synthesiser, and Dr. Frank Owens and Sean Murphy of the University of Ulster, Jordanstown for helping me obtain speech data. Thanks to all my fellow Post-Grads for the crack, coffee, pool and crosswords, and finally to my parents, without whom this would never have been written.

CHAPTER 1 INTRODUCTION

1.1 Coding of Speech at low bit rates

Despite the fact that high bandwidth channels and networks are becoming more viable, coding speech at low bit rates has retained its importance. Specific applications include:

(i) Digital encryption i.e. situations where high security is required over low data rate channels such as radio links.

(ii) Cases where memory efficient systems for voice storage e.g. voice mail are required.

(iii) Mobile telephony. In this case more users can be accommodated on cellular radio or satellite links.

Developers of digital speech coders strive to optimize the interplay of four parameters: bit rate, quality, complexity and delay time. As bit rate is reduced, quality naturally drops off, unless complexity is increased. At high bit rates e.g. 64Kb/s, used in pulse code modulation, quality is not a problem, but it is believed that high quality coding may eventually be practical at rates as low as 2Kb/s [4].

There are two main types of coders:

(i) Waveform coders, which attempt to send an approximation of the speech signal.

(ii) Vocoders (*Vo*ice *Coders*), which attempt to model the speech production mechanism directly, and send parameters which accurately describe the speech production process.

Vocoders results in a drastic reduction in bit rates, and are of primary importance for speech coding.

1.2 Vocoders

In the basic vocoder synthesiser, it is assumed that speech is generated by a vocal tract filter being excited by either a regular pulse source or random noise. Spectral coefficients specifying the vocal tract filter response define the speech formants, while pitch and voicing are defined by the pitch value and a binary voiced / unvoiced decision to select the source of excitation.

There are two main types of vocoders:

(i) **Channel Vocoders:** In this type, typified by Holmes [1], there are typically 15-20 channels, each being a spectrum analyser consisting of a bandpass filter, a rectifier and a low pass filter. These are used to determine the spectral shape.

(ii) **LP (Linear Predictive) Vocoders:** This type is based on linear predictive coding (LPC), a speech analysis method first introduced by Atal *et al.* [2]. Coefficients of an N-pole digital filter, determined from LPC analysis, are used to describe the speech.

In both cases, a pitch value and voicing parameter are extracted simultaneously. In general, speech quality for the two types are comparable with the signal processing required somewhat greater for the channel type [3].

Features of the above basic vocoder types impose fundamental limitations on the speech quality obtainable. The main restricting features are:

(i) Regular pulses for the voiced excitation

(ii) Binary voicing decision - the synthesised speech can only be purely voiced or unvoiced.

Both the above lead to an artificial quality. It is generally agreed that LPC is based on a clearly oversimplified model of the voice source [5], although this simplification gives the advantage that a direct and efficient analysis can be used.

1.3 Articulatory Vocoders

An alternative approach to the general vocoder approach design is to use articulatory parameters for coding speech. As well as providing an economical description of speech, an articulatory vocoder has the following advantages over traditional vocoders:

(i) Articulatory parameters model speech production directly, thus inherently incorporating physiological constraints that exist in the human vocal tract. For example, transitional effects due to tongue and jaw inertia may be modelled directly. An articulatory synthesiser has the potential to produce natural sounding speech at bit rates below 4800b/s.

(ii) The coding (including excitation) parameters have a physiological base and vary slowly. A parametric model of voiced excitation i.e. a glottal source model is usually incorporated in an articulatory vocoder. This overcomes the disadvantages of a binary voicing decision.

(iii) Interpolation between parameters (shapes) result in physically realisable intermediate shapes, which is not always the case for LPC parameters. Slightly erroneous parameters do not usually result in unnatural speech.

Flanagan [3] has extolled the possibilities of an articulatory vocoder, and recommended it above other types. However, the success of an articulatory vocoder is dependent on how accurately articulatory data may be obtained from the speech signal. Much research has been done into this problem, however results have mainly been used for speech recognition, and surprisingly little knowledge has been applied to articulatory vocoding. The simplest type of articulatory vocoders use area functions obtained from direct speech analysis (LPC) as the parameters, which offers no significant advantage over traditional vocoder types. At the other end of the scale is a vocoder recently developed by Sondhi types. At the other end of the scale is a vocoder recently developed by Sondhi *et al.*, based on their extremely complex speech synthesiser [4], the parameters of which are difficult to obtain from the speech signal. One of the main problems of this type is that its voicing parameters have a physiological base, the detail of which introduces many problems for speech analysis.

To extract the source excitation (glottal signal), the vocal tract model estimated from the speech wave must be very accurate. Thus a method which extracts the true glottal waveform would simultaneously extract excellent parameters to represent the vocal tract transfer function. From these vocal tract parameters an accurate representation of the vocal tract shape, and hence positions of the articulatory organs may be estimated.

1.4 Thesis Overview

In this thesis, a compromise between the two extreme articulatory vocoder types is proposed, and a quality articulatory vocoder for vowels sounds is designed. The glottal waveform is extracted from the speech wave by a technique generally known as glottal inverse filtering. Specifically, this involves a modified type of linear predictive analysis. Conventional LPC methods are first detailed, and from these, methods for extracting an accurate vocal tract shape for vowels are developed and compared. Closed glottal interval covariance analysis is investigated, and a new improved algorithm is presented for the method. This method is compared to pitch synchronous and asynchronous analyses which use the autocorrelation method with various types of preemphasis.

The application of vector quantization to articulatory coding is then discussed, and a comparison of suitable distortion measures undertaken. A distortion measure, based on one developed for the autocorrelation method of LPC, but modified for the covariance method, is then proposed. The results of the comparisons are later taken into account in determining the best acoustic match for constructing a codebook.

The construction of an articulatory codebook, and methods for quantizing articulatory parameters are discussed. The idea of a linked codebook of acoustic and articulatory parameters is presented, and one is generated, based on synthetic speech. A natural follow-on, using real speech, is proposed, and methods for constructing such a codebook discussed. This prompts a discussion on methods of obtaining the articulatory parameters directly from the speech wave, and one of these methods is investigated in detail.

Finally, methods for improving the existing set-up are proposed, and possibilities of its extension to other types of speech sounds are outlined. Directions for future research are proposed.

2. THE MECHANISM OF SPEECH PRODUCTION

2.1 Introduction

In this chapter, the human physiological speech production process in relation to vowels, is presented. The generation of voiced source excitation, and the articulation process are discussed. Articulatory models, which attempt to model this process to reproduce the acoustic speech waveform, are reviewed. Finally, an introduction to ASY, the articulatory synthesiser used in this research, is presented. This chapter forms the background to Chapter 3, which examines the acoustic process of speech production.

2.2 Human speech production

Voiced speech waveforms are generated by a speech production process consisting of two main parts:

(i) Voice source generation

(ii) Articulation

The machinery involved is shown in Fig 2.1.

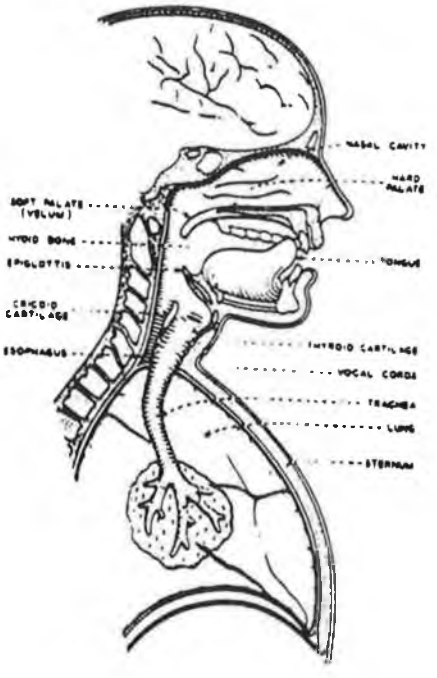


Fig. 2.1 The human speech production mechanism [3]

2.2.1 Voice Source Generation

The energy source for speech production is the respiratory system pushing air out of the lungs. The air passes through the trachea and vocal cords of the larynx into the pharynx (throat cavity) and mouth. The voiced sounds of speech are produced by the vibratory action (i.e. phonation) of the vocal cords. The larynx is also known as the voice box, as its purpose is to hold the vocal cords in the correct position and tension for phonation. The orifice between the cords is known as the glottis. The vocal cords are suspended within a cage of cartilage, and by using a set of muscles attached to this cartilage, they can be moved as required. The action proceeds as follows:

Assume initially that the cords are together. The subglottal pressure increases, forcing them apart. As the air flow through the cords increases, the local pressure drops, according to the Bernouilli effect, and this results in the cords being sucked together again. Thus quasi periodic pulses of air excite the vocal tract for voiced sounds.

The pitch (frequency of oscillation) depends on both the vocal cord tension and their mass per unit length. The volume of air through the glottis as a function of time is roughly proportional to the area of glottal opening. The waveforms are approximately triangular in shape, and typical duty cycles (i.e. ratio of open time to total period) are of the order of 0.3 to 0.7. The glottal waveform shape varies greatly for a given individual, depending on sound pitch and intensity. The pitch normally ranges from 50 - 200Hz for men, with women and children an order of an octave higher.

2.2.2 Articulation

The vocal tract is a nonuniform acoustic tube formed by the articulatory organs. It begins at the glottis and ends at the mouth. It is connected to the nasal tract, which stretches from the velum to the nostrils. The velum controls the acoustic coupling between the tracts, i.e. when it is open the tracts are coupled acoustically, and nasalized sounds are produced. The tract accentuates certain frequencies by resonance, producing each sound with an individual quality. This process is called articulation.

From observation, vowel sounds are dependent on the vocal tract shape as a whole, and may be characterised by three parameters:

(i) the minimum cross–section area, usually at the tongue hump

(ii) the distance of (i) from the glottis, and

(iii) the magnitude of the lip opening.

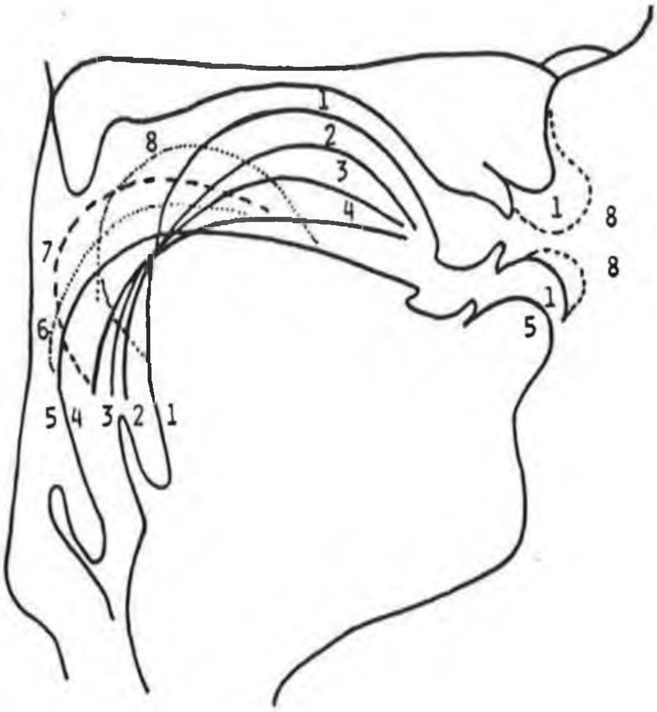


Fig 2.2 Corresponding positions in the tract for vowels in the words: (1) "heed", (2) "hid", (3) "head", (4) "had", (5) "hod", (6) "hawed", (7) "hood", (8) "who'd" [5]

These characteristic shapes are produced by the movement of a combination of articulators, i.e. the tongue, jaw, lips, and to a lesser extent the velum. The position of the tongue separates vowels into front/back and high/low classifications. Klatt [6] also used a lip classification i.e. rounded/unrounded. For nonnazalized voice sounds, the velum is closed. The physiological basis for these classifications may be seen in Fig 2.2. A rapid transition from one vowel to another is known as a dipthong.

Following articulation, the speech is radiated at the mouth. The acoustic consequences of lip radiation are discussed in Chapter 3.

2.3 Models for speech production.

All speech utterances, however varied, have one unifying factor - their origin, the human speech production process. For this reason, the advantages of mimicking this process are many - such problems as speaker differences, accents and coarticulation effects may be overcome by accurate modelling. Hence speech production modelling is a very active area of speech research, contributing to more natural sounding speech synthesis, better recognition rates, and improved coding quality. Models for speech production consist of two parts, the excitation of the vocal cords, and the articulators of the tract.

2.3.1 Source models

Source models vary greatly in detail and accuracy. The most realistic physiologically based model of the vocal cords is Ishizaka and Flanagan's two mass model [7], shown in Fig 2.3.

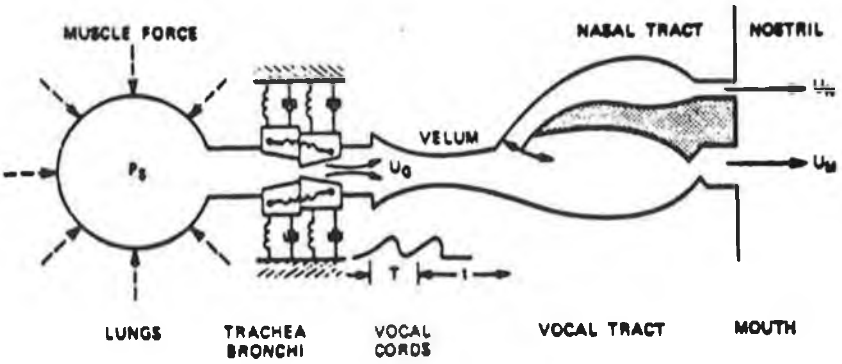


Fig 2.3 Flanagan's Two - Mass Model [7]

The model is a non-linear system, dependent on the supraglottal pressure in the vocal tract. Thus, it accounts for the interaction between the glottal volume velocity and the input impedance of the vocal tract. Each vocal cord is described by two masses, with associated stiffnesses and losses. For voiced sounds

$$R_{tot}\, u_g + L_{tot} \frac{\delta u_g}{\delta t} = P_s - P_1 \qquad (2.1)$$

where P_S is the lung (subglottal) pressure, P_1 is the supraglottal (vocal tract) pressure, and u_g is the volume velocity. R_{tot} and L_{tot} are the total quasi-stationary resistance and inductance representing the expansion and contraction of the vocal cords and are dependent on both the glottal area and the area of the first section of the vocal tract.

The model parameters are the lung pressure, vocal cord tension, and glottal opening area. Both the pitch and glottal waveform are dependent on the lung pressure and glottal rest area. The pitch is controlled by the vocal cord tension.

The effect of the acoustic properties of the trachea and lungs have been shown to be minor by Wakita and Fant [8], and are ignored. Experiments with one-mass models found that the source tract interaction was very dependent on the assumed intraglottal pressure distributions [3], while experments with multi-mass models [10] found they were no better than the two-mass model, in fact they overemphasised source tract interaction.

While this model produces very natural sounding speech, and is the most accurate developed, limited knowledge of the voice anatomy and the difficulties of obtaining the model parameters from the speech wave has meant that more simplified glottal models are often used. These model the glottal waveform, rather than its physiological base [10].

2.3.2 Articulatory models

The design of articulatory models i.e. those which attempt to model the movement of articulators directly, has always been a prominent area of speech research. The first articulatory model of significance was developed by Stevens and House [11], who presented the three parameter model described earlier, representing the vocal tract shape for English vowels. Using this, Fant [12] attempted to reconstruct speech spectra based on X-ray data for Russian vowels.

Initially, tract models for speech synthesis [13] used area functions as input. Following the success of Stevens and House, however, models controlled by articulators have been developed. This approach supports the view that the value of an articulatory model is to what extent it can produce significant detail in its output from simple inputs. Articulator movements try to match the vocal tract shape rather than resolve individual muscles. For the generation of most articulatory shapes, a model with seven to ten degrees of freedom should suffice. Coker's model [14] uses independent and semi-independent articulators, e.g. (tongue tip relative to tongue body). A target approach is used where the motion of each articulator is characterized by a time constant dependent on its weight and the available muscular forces. Like Coker's model, Mermelstein's [15] attempts to match real X-ray data. Although similar in many respects, each places a different emphasis on speech production. Coker's, through incorporating a dynamic controller, stresses synthesis by rule, while the latter concentrates on interactive and systematic control of articulatory configurations and the subsequent acoustic and perceptual effects.

2.4 The ASY Synthesiser

ASY,the research synthesiser developed by Rubin and Baer [16] using Mermelstein's model, is used in this project.

2.4.1 Mermelstein's Model

The movable articulators in this model (see Fig 2.4), are the tongue, jaw, lips, velum and hyoid.

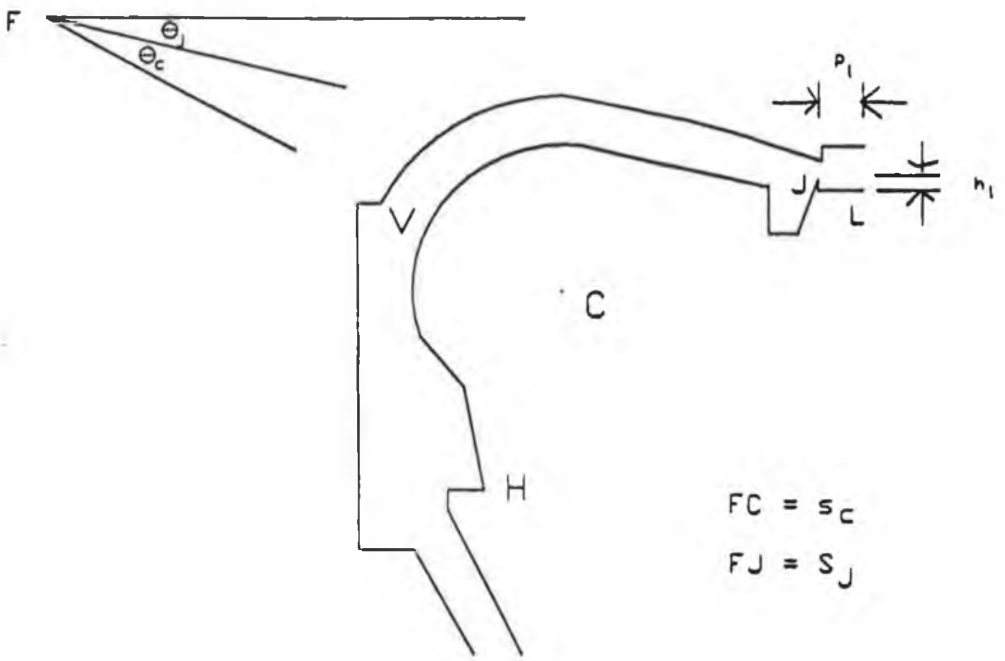


Fig 2.4 Mermelstein's Model

These are surrounded by a fixed structure consisting of the rear pharyngeal wall andthe maxilla, which limits the range of the articulators for consonant articulations. The emphasis when developing the model was manual matching with X-ray tracings obtained from Perkell [17]. The specification of the key articulator positions completely determines the vocal tract outline. These are described as follows:

(i) The **jaw** is defined by its location, J, (in polar coordinates s_j and θ_j) relative to to the fixed point F ; s_j is usually constant.

(ii) The **hyoid** has horizontal and vertical coordinates at point H, such that below H the curve is a function of H alone. The hyoid does not move much for vowels.

(iii) The **tongue body** outline is represented by a circle of moving centre and fixed radius, with polar coordinates (s_c and θ_c) referenced to FJ. This makes its position dependent on jaw movement as well as moving independently.

(iv) The **tongue tip and blade** move relative to the tongue body. The tip appears to rotate about point B so is defined by polar coordinates (s_t and θ_t) relative to B. The blade outline is a curve represented by a radial coordinate. For vowels, this is simplified, where it is effectively only a function of jaw and tongue body coordinates.

(v) The **lips** open and protude relative to the jaw and maxilla. These positions are described by the height and protrusion, respectively h_l and p_l.

(vi) The **velum** opens for nasals, and may be ignored for vowel production.

The anterior outline of the **pharynx** was observed to be controlled by the hyoid and tongue body positions and this is incorporated in the model. The rigid outline was accurately matched with X-ray tracings. By imposing a grid structure on the resulting outline, the area of function of the tract may be determined, with the help of previously published data to closely match the vocal tract shape. Section lengths of 0.875cm are produced, with the number of discrete area sections (and hence vocal tract length) dependent on the particular configuration. The acoustic properties of the synthesiser (i.e. its transfer function) are discussed in section 3.3

2.4.2 Source Excitation for ASY

A time domain acoustic waveform, representing U_g, is used to excite the vocal tract, which can be represented by time varying parameters. These parameters are based on the Rosenberg model [18] of glottal pulse excitation, shown in Fig 2.5, and are:

(i) pitch period T (= 1 / fundamental frequency),

(ii) amplitude α,

(iii) duty cycle i.e. ratio of open time to pitch period, = Tp/T

(iv) speed ratio i.e. ratio of rise time to fall time, = Tp/Tn

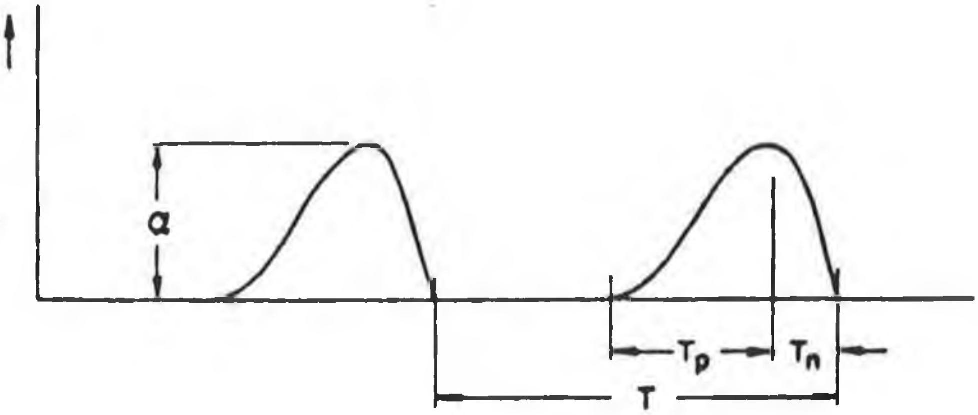


Fig 2.5 Model for the glottal pulse [18]

3. SOUND PROPOGATION IN THE VOCAL TRACT.

3.1 Introduction

In this chapter, the acoustic properties of the vocal tract described in Chapter 2 are presented. Using various assumptions, the transfer function of the vocal tract is derived, and reflection coefficents which describe the acoustic sound propogation through the tube are derived in terms of the cross-sectional area of the tube. The transfer function of the ASY synthesiser is then described.

3.2 Sound Propogation

To analyse the propogation of sound through it, the vocal tract is modelled as a nonuniform, time-varying cross-section tube. For frequencies corresponding to wavelengths that are long in comparison to the tract dimensions, plane wave propogation of sound along its axis may be assumed. Assuming no viscous or thermal conduction losses in the air or the tract walls, the sound waves in the tube satisfy Portnoff's equations [19]:

$$-\frac{\delta p}{\delta x} = \rho \frac{\delta(u / A)}{\delta t} \qquad (3.1a)$$

$$-\frac{\delta u}{\delta x} = \frac{1}{\rho c^2} \cdot \frac{\delta(u/A)}{\delta t} + \frac{\delta A}{\delta t} \qquad (3.1b)$$

where

c = velocity of sound;

p = $p(x,t)$ = variation in sound pressure, position x, time t;

u = $u(x,t)$ = corresponding change in volume velocity;

ρ = density of air in tube;

A = $A(x,t)$ = cross (X) - section area normal to axis of the tube.

Boundary conditions are imposed at either ends of the tube: accounting for sound radiation at the lips and the nature of the excitation at the glottis.

Closed form solutions of eqns. (3.1) are not possible, however numerical solutions may be obtained. The area function A(x,t) must be known, whether from detailed direct measurements, or from the speech wave. The solution is very complicated, thus various assumptions are made.

The vocal tract is regarded as a series of tubes, each of constant cross–section. As the vocal tract changes slowly, it is reasonable to assume the areas are constant over a short space of time i.e. the analysis interval (20 - 30ms). Thus for each section

$$A(x,t) = A = \text{constant.} \qquad (3.2)$$

Thus for the mth uniform tube, eqns. (3.1) are simplified into difference equations to give a solution of the form:

$$u_m(x,t) = [\, u_m^+(t - x/c) - u_m^-(t + x/c) \,] \qquad (3.3a)$$

and

$$p_m(x,t) = [\, p_m^+(t - x/c) + p_m^-(t + x/c) \,] \qquad (3.3b)$$

which are interpreted as forward and backward travelling waves, with the centre of each section defined as x = 0, as shown in Fig 3.1.

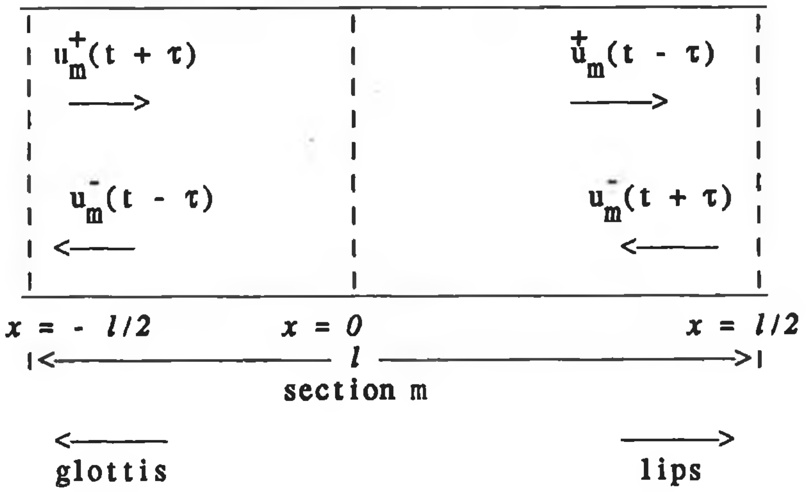


Fig 3.1 Forward and reverse volume velocity waves in section m.

From eqn. (3.3), and using Portnoff's equations, a relationship between pressure and volume velocity may be derived, i.e.

$$p_m\ (x,t) \quad = \quad \frac{\rho c}{A_m}\ .\ [\ u_m^{+}(t\ -\ x/c)\ -\ u_m^{-}(t\ +\ x/c)] \qquad (3.4)$$

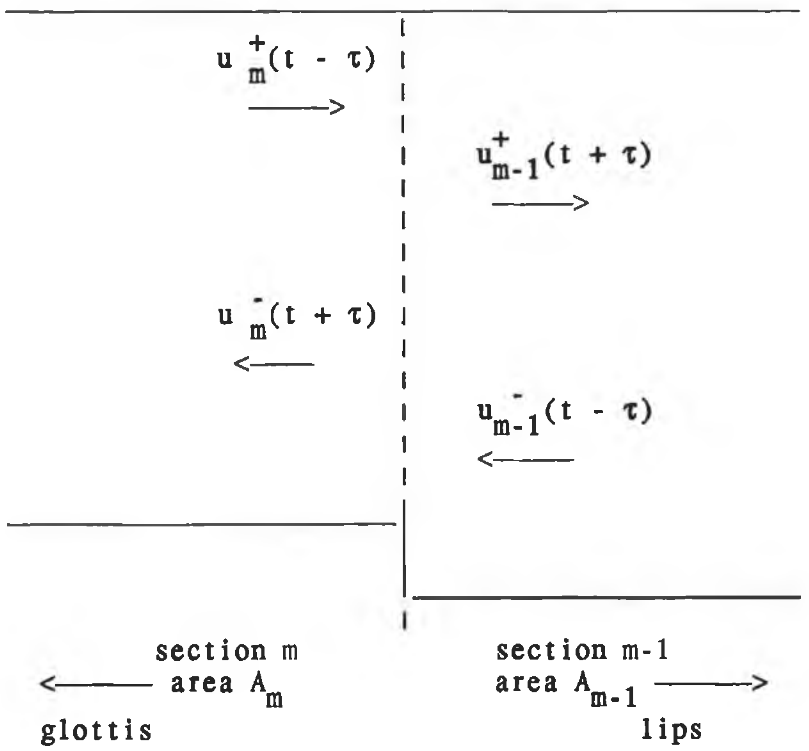


Fig 3.2 Continuity conditions for volume velocity between section m and section m - 1.

Examining the continuity considerations between boundaries, shown in Fig 3.2, and defining the time taken for a wave to propogate half way along a section as

$$\tau \quad = \quad 2l\ /\ c \qquad (3.5)$$

it follows that

$$-\ u_m^{-}(t\ +\ \tau) \quad = \quad \frac{A_{m-1}\ -\ A_m}{A_{m-1}\ -\ A_m}\ .\ u_m^{+}(t\ -\ \tau) \qquad (3.6)$$

and from this a reflection coefficient may be defined:

$$\mu_m = \frac{A_{m-1} - A_m}{A_{m-1} - A_m} \tag{3.7}$$

or

$$\frac{A_m}{A_{m-1}} = \frac{1 - \mu_m}{1 + \mu_m} \tag{3.8}$$

For the tubes at either end, boundary conditions are imposed. From Wakita [20], the acoustic tube is assumed open at the lips, i.e. zero radiation impedance

$$\mu_0 = 1 \tag{3.9}$$

From this, the volume velocity at the lips is

$$u_L(t) = 2\, u_0^+ (t - \tau) \tag{3.10}$$

At the glottis end, assuming a volume velocity $u_g(t)$ with source impedance Z_g, the glottal area is defined as

$$A_M = \frac{\rho c}{Z_g} \tag{3.11}$$

3.2.1 Transfer function in the sampled time domain

The transfer function of the vocal tract will now be developed in terms of μ. Defining

$$c_m = \prod_{i=1}^{m} (1 + \mu_i) \qquad m > 0 \quad , \quad c_0 = 1 \tag{3.12a}$$

and

$$t_m = 2\,(m + 1)\tau . \tag{3.12b}$$

a new variable {y} is introduced such that

$$y_m^+(t) = c_m\, u_m^+(t + \tau - t_m) \tag{3.13a}$$

$$y_m^-(t) = - c_m\, u_m^-(t + \tau - t_m) \tag{3.13b}$$

Sampling at T = 4τ, manipulating and obtaining the Z - transforms of eqn (3.13) results in

$$Y_{m+1}^+(z) = Y_m^+(z) - \mu_{m+1} Y_m^-(z) \tag{3.14a}$$

and

$$Y_{m+1}^-(z) = z^{-1} [Y_m^-(z) - \mu_{m+1} Y_m^+(z)] \tag{3.14b}$$

These expressions will be used to establish a relationship between the acoustic tube model presented here and the LPC model of Chapter 4.

3.3 Transfer function of the ASY synthesiser

The transfer function for ASY is derived in a similar fashion to the model above. However its boundary conditions are different, and it incorporates propogation losses dependent on each X-section area. The attentuation (propogation loss) α is defined as

$$\alpha^{1/2} = 1 - 0.007\,(A)^{1/2} \tag{3.15}$$

Non ideal terminations are accurately accounted for. The radiation at the lips is represented by a non-zero radiation impedance Z_r, which consists of a parallel RL circuit i.e.

$$Z_r = \frac{1 - z^{-1}}{[\,2 / R + 0.7(1 - z^{-1})]} \tag{3.16}$$

where

R = effective radius of lips = (A_0 / π).

The glottal impedance Z_g is modelled by a series RL circuit,where R_g and L_g are dependent in the glottal area, and averaged over an interval, similar to the glottal impedance discussed in Section 2.3.1. They are adjusted to account for effects of yielding vocal tract walls. In the default state, $R_g = 50\Omega$ and $L_g = 1200\Omega$

4. LINEAR PREDICTIVE CODING OF SPEECH

4.1 Introduction

In this chapter, the fundamental concept of Linear Predictive Coding (LPC) is introduced, and its suitability to speech acoustics discussed. The basic equations of LPC are derived, and various formulations are presented for their solution. In particular, solutions for the autocorrelation and covariance methods are derived, and the relationship between these and the lattice method derived. Then the lattice formulation, by showing how the area functions of the vocal tract may be obtained from its results, unifies the acoustic tube model of Chapter 3, and the waveform analysis here. These solutions form the basis of the analysis of the next chapter.

4.2 LPC Model for speech production

In order to efficiently analyse speech at an acoustic level, a knowledge of speech production is essential. A suitable model of speech production is presented here which leads to linear predictive analysis of the speech waveform.

Speech waveforms are the result of the vocal tract being acoustically excited. The vocal tract may be represented by a slowly time varying linear filter. For most sounds, particularly voiced, the tract changes slowly, and the speech may be considered to be stationary over a short interval (e.g. up to 20ms). For this reason, it may be modelled by a digital filter, whose parameters are updated at regular at regular intervals. The tract is excited by the volume velocity waveform from the glottis. In the case of voiced speech, this wave is smooth and periodic, whereas for unvoiced speech, it corresponds to random white noise. This source - filter model of speech production, shown in Fig 4.1, leads to a simple and effective method of speech synthesis and coding.

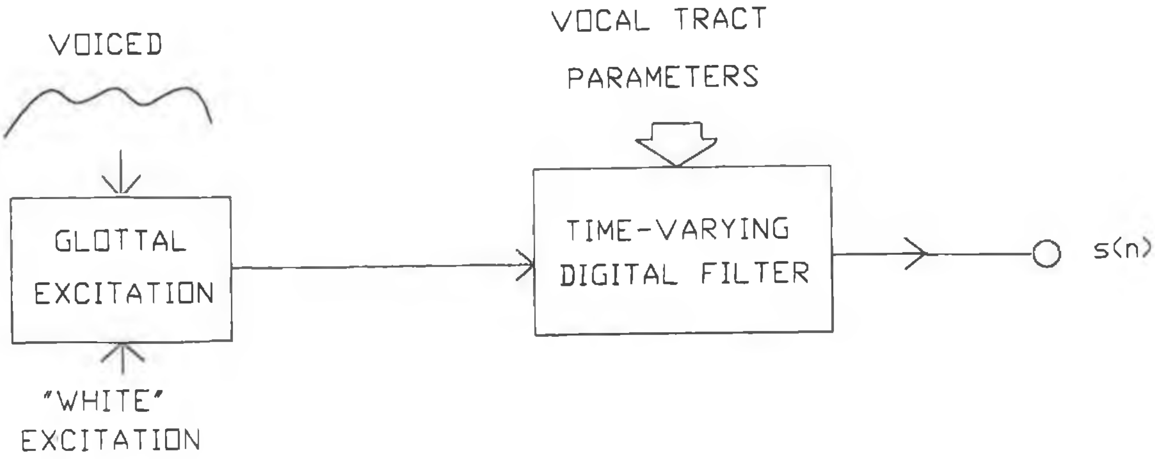


Fig. 4.1 Source-Filter Model of Speech Production

For LPC, the model may be further simplified by representing the combined spectral contributions of glottal flow, the vocal tract, and radiation at the lips into a single time varying all pole filter (see Fig 4.2). The filter is excited by either a series of periodic pulses generated by the vocal cords (in the case of voiced speech), or random noise (unvoiced). Thus the difficult problem of separating the source from the speech spectrum is bypassed.

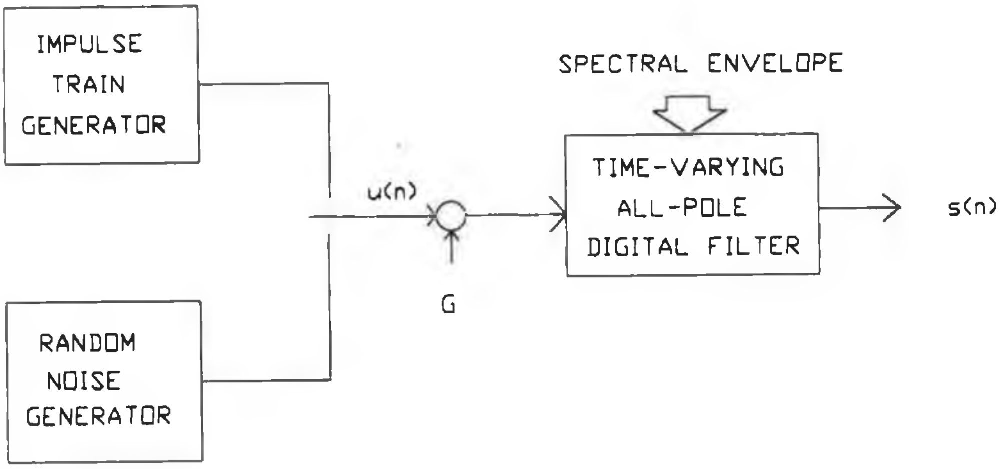


Fig. 4.2 Linear Prediction Model of Speech Production

An all-pole filter model represents the vocal tract quite accurately and extra poles compensate for zeros in the spectrum (which occur in nasals). By avoiding zeros, the filter parameters may be readily determined.

Thus the transfer function of the all-pole filter is of the form

$$H(z) = \frac{1}{1 - \sum_{k=1}^{M} a_k . z^{-k}} \qquad (4.1)$$

where $\{a_k\}$ are the coefficients of the digital filter.

In the time domain, the speech samples s(n) are related to the excitation u(n) by the simple difference equation

$$s(n) = \sum_{k=0}^{M} a_k . s(n - k) + G\ u(n) \qquad (4.2)$$

where G is the gain.

This is in the form of a linear predictor i.e. the essence of LPC is that, due to the high correlation between adjacent speech samples, a sample s(n) may be approximated as a linear combination of previous samples i.e.

$$\tilde{s}(n) = \sum_{k=0}^{M} \alpha_k\ s(n - k) \qquad (4.3)$$

Using this approximation, the prediction error is

$$e(n) = s(n) - \tilde{s}(n) = s(n) - \sum_{k=0}^{M} \alpha_k .\ s(n - k) \qquad (4.4)$$

If $\alpha_k = a_k$, then e(n) = G u(n) is the output of a system having transfer function

$$A(z) = 1 - \sum_{k=1}^{M} a_k . z^{-k} \tag{4.5}$$

and since e(n) = G u(n), the prediction error filter is an inverse filter for H(z) i.e.

$$H(z) = \frac{1}{A(z)} \tag{4.6}$$

and

$$\frac{S(z)}{E(z)} = H(z) \tag{4.7}$$

Thus the basic problem of LPC is to find a set of predictor coefficients which minimise the mean squared error over a finite interval. These coefficients are obtained by partially differentiating

$$E = \Sigma\, e(n)^2 \tag{4.8a}$$

i.e.

$$\frac{\delta E[\ e(n)\ ]^2}{\delta a_k} = 0 \qquad k = 1...M \tag{4.8b}$$

with respect to each a_k and setting the result equal to zero. This leads to a set of simultaneous linear equations:

$$\sum_{k=0}^{M} a_k \sum_{n} s(n - k).s(n - i) = \sum_{n} s(n - i).s(n) \ , \ 1 \leq i \leq M \tag{4.9}$$

Defining

$$\Psi(i,k) = \sum_{n} s(n - i).s(n - k) \tag{4.10}$$

this can be simplified to

$$\sum_{k=1}^{M} a_k . \Psi(i,k) = \Psi(i,0) \qquad 1 \leq i \leq M \tag{4.11}$$

4.3 Solution of LPC

Ideally, the mean squared error of eqn. (4.8) should be minimized over an infinite interval, but this cannot be used in practise. The definition of the range of minimization of the error leads to separate approaches to LPC. Many different solutions exist for the solution of eqn. 4.11. Four are discussed in this research:

(i) Prony's method [21]

(ii) Autocorrelation method [21,22]

(ii) Covariance method [23]

(iv) Lattice method [24]

4.3.1 Prony's method

Prony's method is very old, and is important in understanding linear prediction of speech as it shows explicitly how the voiced speech model may be represented by complex exponentials in the time domain.

The speech model during voicing corresponds to a sequence of unit samples (separated by the pitch period) driving an all-pole filter 1/A(z). If transients from preceding pitch periods are ignored, voiced speech samples during the period will be proportional to the unit sample response of an all pole filter. Thus the sampled speech data {s(n)} may be modelled as a linear combination of M complex exponentials, i.e.

$$s(n) = \sum_{i=1}^{M} u_i \, (z_i)^n \tag{4.12}$$

where z_i, i = 1,..M defines roots or zeros of A(z):

$$A(z_i) = 0 \qquad i = 1,..M. \tag{4.13}$$

With the driving sequence $e(n) = \delta_{n0}$

$$S(z) = \frac{E(z)}{A(z)} = \frac{1}{A(z)} \tag{4.14}$$

If speech were precisely representable by the model of eqn. (4.12), the unknowns u_i and z_i (2M in number) could be obtained by solving the set of 2M simultaneous equations. Thus if a signal s(n) is composed of precisely M complex exponentials, then 2M samples suffice to exactly determine the model parameters.

As M becomes large, the solution to these equations becomes unwieldly. To avoid solving them, another approach is :

$$S(z)\ A(z) = P(z) \tag{4.15}$$

or

$$\sum_{i=0}^{M} a_i\ s(n - i) = \sum_{i=0}^{M-1} p_i\ \delta_{n,i} \tag{4.16}$$

so

$$\sum_{i=0}^{M} a_i\ s(n - i) = 0 \qquad n = M,...N-1 \tag{4.17}$$

To account for the possibility that the model may not exactly represent a single pitch period of real speech, an error term is introduced so

$$\sum_{i=0}^{M} a_i\ s(n - i) = e(n) \qquad a_0 = 1 \tag{4.18}$$

So $\{a_i\}$ are obtained by minimizing the squared error α where

$$\alpha = \sum_{n=M}^{N-1} e(n)^2 \tag{4.19}$$

which will be shown to be the same result as the covariance method. In this case, zeros are also allowed i.e. P(z) is not necessarily equal to 1.

4.3.2 Autocorrelation method

In this method, the speech samples are assumed to be zero outside a certain interval N, i.e. a windowing procedure is used:

$$s_w(n) = s(n) \; . \; w(n) \tag{4.20a}$$

where

$$w(n) = 0 \qquad n < 0 \quad \text{and } n > N - 1 \tag{4.20b}$$

In this case the limits of summation for **E** are

$$E = \sum_{n=0}^{N+M-1} e^{2}(n) \tag{4.21}$$

It can be shown that $\Psi(i,k) = R(i-k)$ where R(k), the short time autocorrelation function is defined as

$$R(k) = \sum_{n=0}^{N+M-1} s_w(n) . s_w(n + k) \tag{4.22}$$

Since $R(i-k) = R(k-i)$, eqn. (4.11) is simplified to

$$\sum_{k=1}^{M} a_k . R(i - k) = R\,(i) \qquad 1 \leq i \leq M \tag{4.23}$$

In matrix form this is

$$\begin{bmatrix} R(0) & R(1) & R(2) & \cdots & R(M-1) \\ R(1) & R(0) & R(1) & \cdots & R(M-2) \\ R(2) & R(1) & R(0) & \cdots & R(M-3) \\ \vdots & \vdots & \vdots & & \vdots \\ R(M-1) & R(M-2) & R(M-3) & \cdots & R(0) \end{bmatrix} \begin{bmatrix} a_1 \\ a_2 \\ a_3 \\ \vdots \\ a_M \end{bmatrix} = \begin{bmatrix} R(0) \\ R(1) \\ R(2) \\ \vdots \\ R(M) \end{bmatrix} \qquad (4.23)$$

4.3.2.1 Solution of the autocorrelation method

The solution of eqn (4.23) is obtained by exploiting the fact that the autocorrelation matrix is a Toeplitz matrix i.e. it is symmetric and all its elements along a given diagonal are equal. Thus, an efficient algorithm may be used for its solution. Many have been proposed [25,26], the most efficient being Durbin's recursive procedure [25]. This may be stated as follows:

$$E^{(0)} = R(0) \qquad (4.25a)$$

$$k_i = \left[R(i) - \sum_{j=1}^{i-1} a_j^{(i-1)} . R(i-j) \right] / E^{(i-1)} \qquad (4.25b)$$

$$a_i^{(i)} = k_i \qquad (4.25c)$$

$$a_j^{(i)} = a_j^{(i-1)} - k_i \; a_{i-j}^{(i-1)} \qquad (4.25d)$$

$$E^{(i)} = (1 - k_i^2) . E^{(i-1)} \qquad (4.25e)$$

Solving these equations recursively for $1 \leq i \leq M$, the final solution is

$$a_j = a_j^{(M)} \qquad 1 \leq j \leq M \qquad (4.25f)$$

The quantity $E^{(i)}$ is the mean squared prediction error for a predictor of order i. It can be shown [21] that the quantities k_i are bounded by unity i.e.

$$-1 \leq k_i \leq 1 \qquad (4.26)$$

and this is a necessary and sufficient condition for A(z) to be stable i.e. for all its roots to be inside the unit circle.

4.3.2.2 Choice of Window

Because of its assumption of zero valued samples outside the analysis interval, the autocorrelation method needs a window. The ideal window should have a high frequency resolution (i.e. its main lobe should be narrow and sharp) and small spurious distortion outside of this lobe (sharp drop off). A Hamming window [27] is normally chosen as it has good frequency resolution and side lobes of less than -40dB. It is of the form

$$w(n) = 0.54 - 0.46 * \cos (2\Pi n / N - 1) \quad 0 \leq n \leq N-1 \qquad (4.27)$$

4.3.3 Covariance method

In this method, an interval of length N is also taken, but no assumptions are made outside this interval, and no windowing is used. Thus E is taken over all except the first M samples, so that samples outside the interval are not used i.e.

$$E = \sum_{n=M}^{N-1} e^2 (n) \qquad (4.28)$$

Here Ψ(i,k) becomes

$$\Psi(i,k) = \sum_{n=M}^{N-1} s(n-i).s(n+k) \qquad (4.29)$$

Ψ(i,k) is a cross-correlation function unlike the autocorrelation function used earlier. From eqn (4.29), eqn. (4.11) may be written as

$$\sum_{k=1}^{M} a_k \Psi(i,k) = \Psi(i,0) \qquad 1 \leq i \leq M \qquad (4.30)$$

which in matrix form is

$$\begin{bmatrix} \Psi(1,1) & \Psi(1,2) & \cdots\cdots & \Psi(1,M) \\ \Psi(2,1) & \Psi(2,2) & \cdots\cdots & \Psi(2,M) \\ \Psi(3,1) & \Psi(3,2) & \cdots\cdots & \Psi(3,M) \\ \vdots & \vdots & & \vdots \\ \Psi(M,1) & \Psi(M,2) & \cdots\cdots & \Psi(M,M) \end{bmatrix} \begin{bmatrix} a_1 \\ a_2 \\ a_3 \\ \vdots \\ a_M \end{bmatrix} = \begin{bmatrix} \Psi(1,0) \\ \Psi(2,0) \\ \Psi(3,0) \\ \vdots \\ \Psi(M,0) \end{bmatrix} \qquad (4.31)$$

4.3.3.1 Solution of the covariance method

The matrix above is symmetric (but not Toeplitz), and has the properties of a covariance matrix, hence the name. An algorithm known as Cholesky decomposition [28] is used here by noting that the covariance matrix Ψ is a positive definite symmetric matrix. Ψ may be expressed in the form

$$\Psi = V D V^{t} \qquad (4.32)$$

where V is a lower triangular matrix and D a diagonal matrix. These are readily determined from above by solving for the (i,j)th element on both sides of the eqn (4.32) giving

$$V_{ij} d_j = \Psi(i,j) - \sum_{k=1}^{j-1} V_{ik} d_k V_{jk} \qquad 1 \leq j \leq i-1 \qquad (4.33)$$

and for the diagonal elements

$$d_i = \Psi(i,i) - \sum_{k=1}^{j-1} V_{ik}^{2} d_k \qquad i \geq 2 \qquad (4.34a)$$

$$d_1 = \Psi(1,1) \qquad (4.34b)$$

Once V and D are determined, a two step procedure is used to solve for {a} i.e.

$$\Psi = V D V^{t} \qquad (4.35a)$$

written as

$$V^t a = D^{-1} Y \qquad (4.35b)$$

where VY = Ψ. Using a simple recursion eqns. (4.35) may be solved for Y i.e.

$$Y_i = \Psi_i - \sum_{j=1}^{i-1} V_{ij} Y_j \qquad M \geq i \geq 2 \qquad (4.36a)$$

with

$$Y_1 = \Psi_1 \qquad (4.36b)$$

4.3.4 PARCOR analysis (lattice method)

This method shows that an intermediate set of parameters is obtainable from the autocorrelation and covariance methods, thus presenting a unified approach to the solutions. Partial autocorrelation (PARCOR) analysis has found uses in many practical applications as it is less disturbed by quantization effects, and is not dependent on the order of analysis used.

The PARCOR formulation defines both forward and backward prediction errors. These are defined respectively as:

$$e_f(t) = s_t - \tilde{s}_t = s_t + \sum_{j=1}^{m} a_i \, s_{t-i} \qquad (4.37a)$$

$$e_b(t-(m+1)) = s_{t-(m+1)} - \tilde{s}_{t-(m+1)} \qquad (4.37b)$$

$$= s_{t-(m+1)} + \sum_{j=1}^{m} b_j \, s_{t-j} \qquad (4.37c)$$

$$= \sum_{j=1}^{m+1} b_j \, s_{t-j} \qquad (4.37d)$$

When {s} is stationary

$$b_j = a_{m+1-j} \qquad j = 1..,m+1 \tag{4.38}$$

PARCOR is defined as the correlation between residual waves that are the remainders of the subtraction of predictable parts utilizing the data between the samples, i.e.

$$k_{m+1} = \frac{\overline{[e_{f,t}]\,[e_{b,t-(m+1)}]}}{\left[\overline{e^2_{f,t}}\right]^{1/2}\left[\overline{e^2_{b,t-(m+1)}}\right]^{1/2}} \tag{4.39}$$

From the above, it can be shown that the relationship between a_i and k_i is:

$$a_i^{(m+1)} = a_i^{(m)} - k_{m+1}\, a_{m+1-i}^{(m)} \tag{4.40}$$

and hence, using earlier formulae,

$$A_{m+1}(z) = A_m(z) - k_{m+1}\, B_m(z) \tag{4.41a}$$

and

$$B_{m+1}(z) = z^{-1}\,[\, B_m(z) - k_{m+1}\; A_m(z)\,] \tag{4.41b}$$

These relations are used to recursively calculate a_m. With $A_0(z)=1$, the inverse filter in terms of $\{B_i(z)\}$ is

$$A_m\,(z) = 1 + \sum_{i=1}^{m} k_i\, B_{i-1}(z) \tag{4.42}$$

Thus, the PARCOR coefficients are derived sequentially in a multi-stage lattice circuit, as shown in Fig. 4.3, hence the name lattice method.

It can be shown by direct substitution that the parameters k_i are identical to those obtained from Durbin's recursion. For the covariance method, they may be determined from a step-up procedure using eqn (4.42).

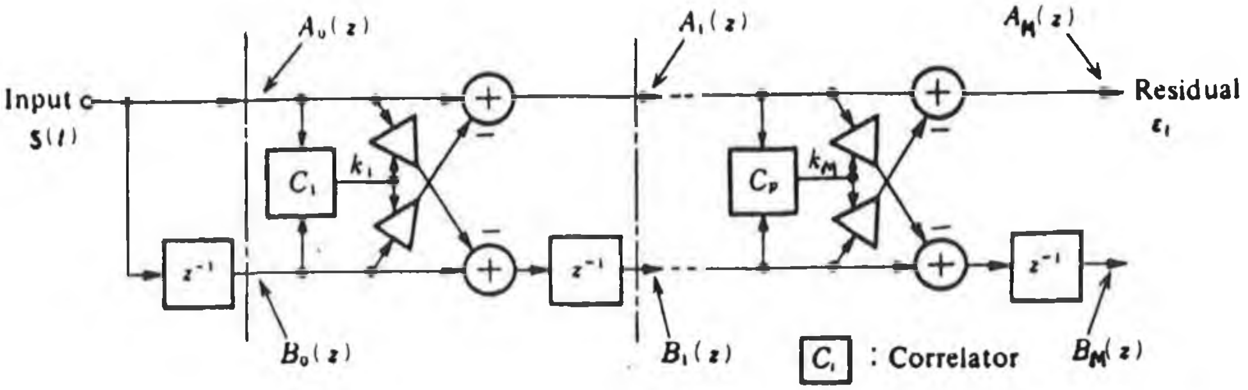


Fig 4.3 Inverse Filter A(z) in the PARCOR formulation

4.4 Relationship between PARCOR analysis and the acoustic tube model

The problem of extracting the vocal tract shape from the acoustic speech waveform has been the subject of much research. From Atal [29], the areas of the acoustic tube model presented earlier can be extracted from formant frequencies and bandwidths, or from an all-pole transfer function. Wakita [20], using the boundary conditions imposed in Section 3.2 in the previous chapter, showed that the same acoustic tube model is equivalently represented by the inverse filter A(z).

This is shown by comparing eqns. (3.14) and (4.41). It can be seen that these transfer functions are equivalent under the following conditions:

(i) $\mu_m = k_m$ (4.43)

(ii) The order of the inverse filter A(z), M, equals the number of acoustic tube sections, M.

(iii) The sampling rate, f_s must be the same for both analyses. From eqn. (3.9), this means

$$f_s = \frac{Mc}{2L} \tag{4.44}$$

(iv) The effect of glottal and radiation characteristics must be removed from the speech waveform before LPC analysis is carried out. This is illustrated in Fig. 4.4, which shows a typical glottal waveform obtained from LPC inverse filtering with no preemphasis. For analysis purposes, the vocal tract system is assumed linear, and ideal boundary conditions are assumed, so these effects have to be removed separately. Methods for removing them are discussed in Chapter 5.

Thus, the reflection coefficients which define the area ratios of the tube may be obtained directly from the speech waveform.

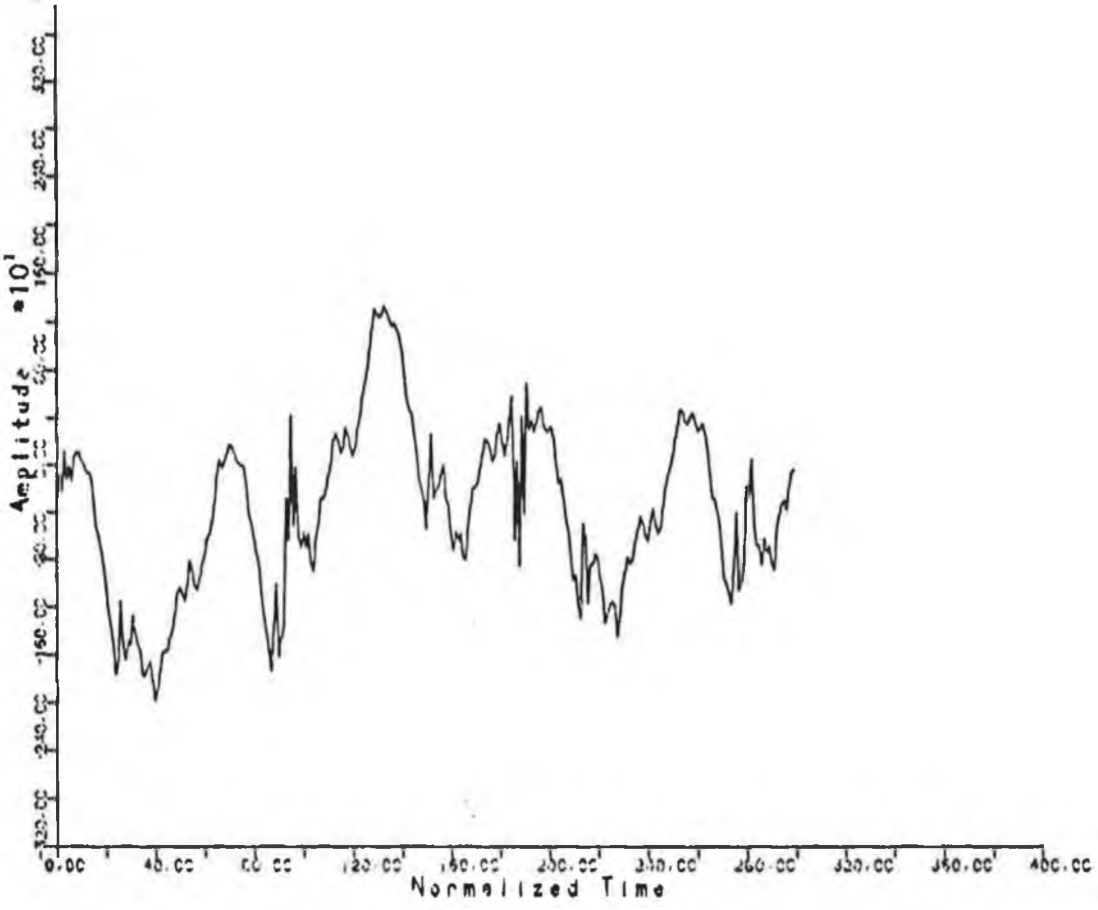


Fig 4.4 Glottal Waveform Obtained using no preemphasis

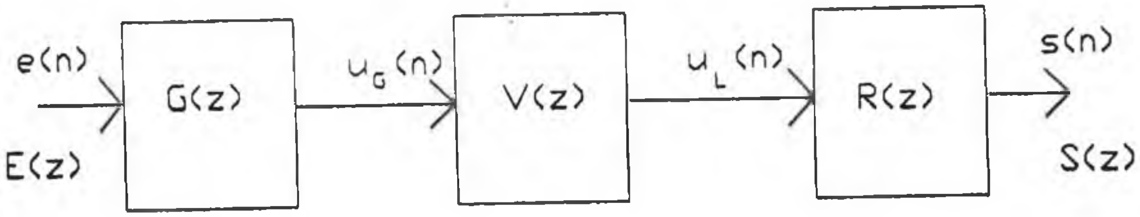
5. ESTIMATION OF THE VOCAL TRACT TRANSFER FUNCTION.

5.1 Introduction

In this chapter, the limitations of the linear prediction model of speech production are discussed, and a more realistic model is introduced. Two classes of methods, based on LPC analysis, for extracting the vocal tract transfer function are proposed. The first type, known as inverse filtering, is based on the autocorrelation method with preemphasis. The second is based on the covariance method over the closed glottis interval. The inadequacies of existing procedures for the covariance method are discussed, and a new algorithm is proposed. Procedures for both methods are outlined, including a robust algorithm for extracting the glottal parameters. Then results for both methods are presented, and a qualitative comparison done. The effects of source tract interaction on both methods is discussed.

5.2 A new model of Speech Production

The speech production model of Chapter 4 for LPC analysis is rather simplistic. The system function H(z) is obtained under the assumption of a voice source with a flat spectrum. Thus it does not directly correspond to the vocal tract transfer function. A more accurate speech production model is shown in Fig 5.1.



5.1 Improved Linear speech production model

The quantities are as follows:

$E(z)$ <—> $e(n)$ = glottal excitation model input

$U_G(z)$ <—> $u_G(n)$ = glottal volume velocity

$U_L(z)$ <—> $u_L(z)$ = lip volume velocity

$S(z)$ <—> $s(n)$ = speech pressure wave

$e(n)$ is a mathematical input to a glottal model filter $G(z)$ to generate $u_G(n)$. For voiced sounds, $e(n)$ is taken to be a a periodic train of pulses, and is the usual LPC input.

Thus

$$S(z) = G(z)\ V(z)\ R(z)\ E(z) \tag{5.1a}$$

$$= G(z)\ V(z)\ R(z) \qquad \text{since } E(z) = 1 \tag{5.1b}$$

where the corresponding system functions are

$G(z)$ <—> source generation

$V(z)$ <—> vocal tract resonance

$R(z)$ <—> radiation from the lips.

Comparing this with the LPC model of eqn. (4.7),

$$H(z) = G(z)\ V(z)\ R(z) \tag{5.2}$$

Thus, to obtain $V(z)$, $R(z)$ and $G(z)$ have to removed. Once $V(z)$ is determined (as discussed in the next section), the corresponding glottal waveform $U_G(z)$ = $G(z)$ may be extracted by first inverse filtering to obtain

$$\frac{H\ (z)}{V(z)} = U_G(z)\ R(z) \tag{5.3}$$

and then approximating $R(z)$ as

$$R(z) = 1 - z^{-1} \tag{5.4}$$

i.e. integrate the residual to obtain the glottal waveform.

5.3 Methods for extracting the vocal tract transfer function

To extract V(z), and hence the true area function, the effects of glottal and radiation characteristics have to be removed. Two main methods exist for estimating V(z) accurately:

(i) Inverse filtering (possibly adaptive), followed by the autocorrelation method.

(ii) Covariance analysis over the closed glottis interval.

5.3.1 Inverse filtering methods.

The pre-processing of the speech signal to remove the effects of G(z) and R(z) is referred to as inverse filtering. Roughly speaking, the source frequency characteristic is -12dB/oct and the radiation is +6dB/oct. Thus H(z) has an approximately -6dB/oct low pass filtering characteristic. To flatten the gross spectral character, the following methods have been proposed:

(i) First order differentiation:

This involves taking a straight difference i.e.

$$y_t = x_t - x_{t-1} \tag{5.5a}$$

i.e.

$$F(z) = 1 - z^{-1} \tag{5.5b}$$

(ii) Adaptive first - order inverse filtering:

This is a low pass filter of the form

$$F(z) = 1 - k_1 z^{-1} \tag{5.6}$$

where k_1 is the first PARCOR coefficient. This may be improved by repeated adaptive inverse filtering until k_1 becomes sufficiently small i.e.

$$F_i(z) = F_{i-1}(z) (1 - k_1^{(i-1)} z^{-1}) \tag{5.7}$$

(iii) Adaptive multi - order inverse filtering:

A comprehensive method has been proposed by Nakajima [30]. It uses a five stage filter, as shown in Fig 5.2. $\{\epsilon\}$ are correlation coefficients determined from the waveform at each stage. The first, second and fourth stages are second order filters which compensate for radiation and source characteristics, while the third (second order), and fifth (third order) stage filters, compensate for the characteristic curvature of the spectrum envelope. Though rather empirically derived, this technique is reported to have yielded very accurate area functions.

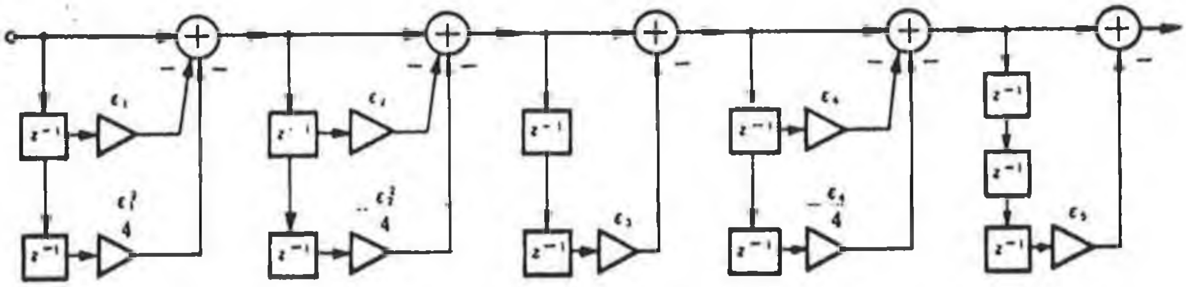
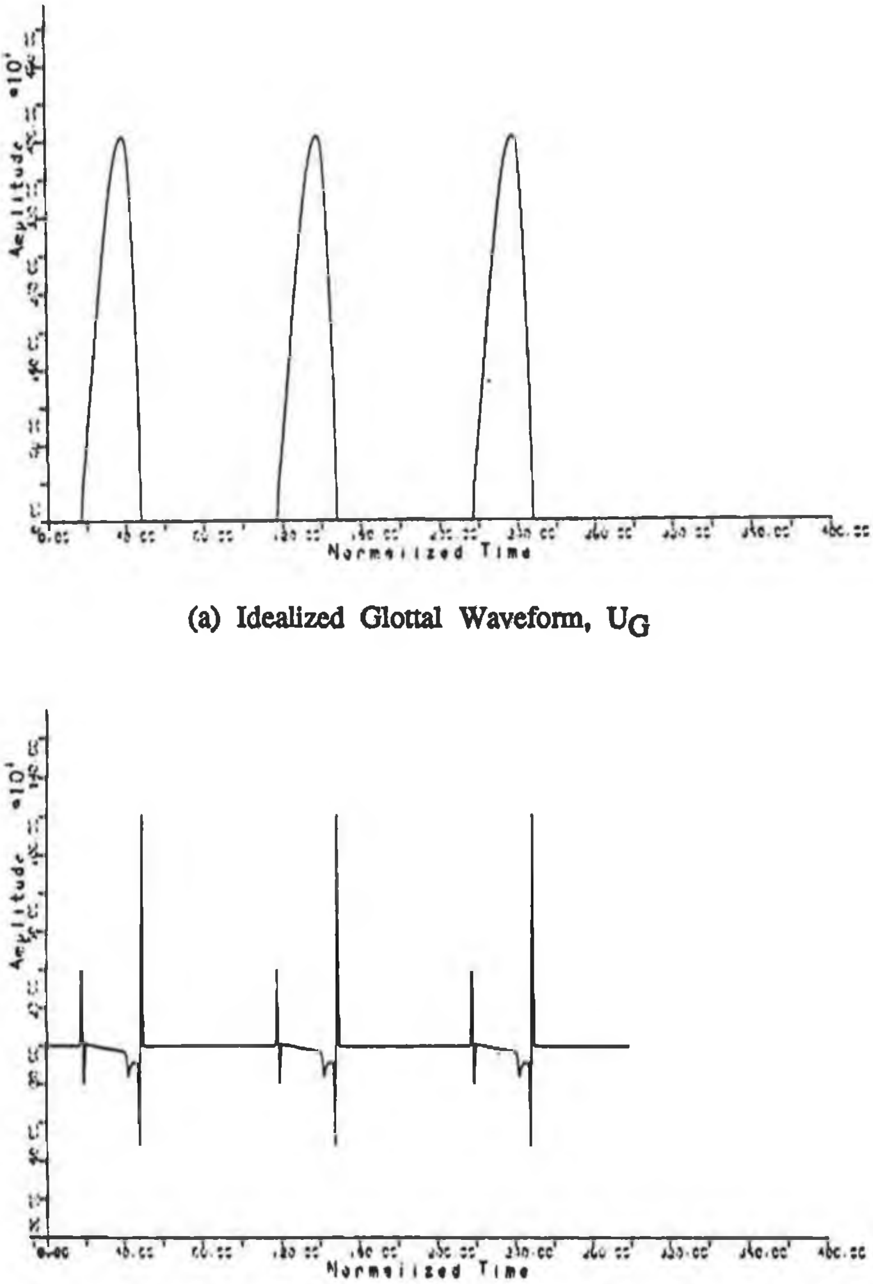


Fig 5.2 Adaptive Multi-Order Multi-Stage Filter.

(iv) Pitch synchronous first order inverse filtering.

In this method [31], the radiation effect is first removed by the preemphasis method (i), i.e. straight differentiation. Then an analysis frame centred at glottal closure is taken to determine V(z). The motivation for this is seen by looking at Fig 5.3. Fig. 5.3a shows an idealized glottal waveform. This waveform is effectively differentiated once during the speech production process (due to lip radiation), and once during preemphasis. Thus the source contribution to the output speech waveform is shown in Fig. 5.3b. Large impulses occur at glottal closure, with smaller peaks at opening. The difference in peak size is due to the fact that glottal waveform at closure is far steeper than at opening. If secondary peaks are ignored, the source contribution in a frame centred at the closure peak will have a flat spectrum (i.e. impulse response), so the spectrum obtained by analysing this frame will be that of the vocal tract alone.



(a) Idealized Glottal Waveform, U_G

Fig 5.3 (b) U_G differentiated twice

By applying a Hamming window, the peaks at opening will be attenuated even further, enforcing the validity of the proposal. In order to avoid the effects of the opening location further, a frame of slightly less length than a pitch frame may be used.

5.3.1.1 Experimental procedures

(i) Preemphasis over a long analysis frame

The algorithm for extracting V(z) by this method is shown in Fig 5.4. This algorithm, and all those following, were implemented in 'C' on a MicroVax computer. The speech in this, and all other, cases was sampled at 7.5Khz. An initial estimate of the pitch is obtained to determine an appropriate analysis frame length, as well as for estimating the glottal parameters later. the chosen preemphasis is carried out, and the frame Hamming-windowed. An overlap of half a frame is used. The LPC predictor coefficients are extracted using Durbin's recursion algorithm (autocorrelation method), as described earlier in Section 4.3.2, with a filter order of M=8. These coefficients are then used in a direct form all-zero filter, V(z), through which the unwindowed, unpreemphasised speech is filtered to obtain the residual signal. This is then integrated over a pitch period, chosen so that the approximate closure point (as depicted from the maximum value of the residual) is towards the end of the interval, so as to facilitate extraction of the glottal parameters. The corresponding formants and bandwidths, are obtained using a root solving procedure for V(z). The area function is obtained from the reflection coefficients of Durbin's recursion.

(ii) Pitch synchronous method.

The algorithm for extracting V(z) by this method is shown in Fig 5.5. In this method, an initial estimate of V(z) is first obtained, as in (i). Again the maximum excitation of the residual is taken as the closure point. This is then used as the centre of a pitch frame. The speech is preemphasised using method (i) and a Hamming window applied, followed by Durbin's recursion. The speech is then inverse filtered to obtain the residual, which in turn is integrated to obtain the glottal waveform, and its corresponding parameters. The formants, bandwidths and area function are then extracted.

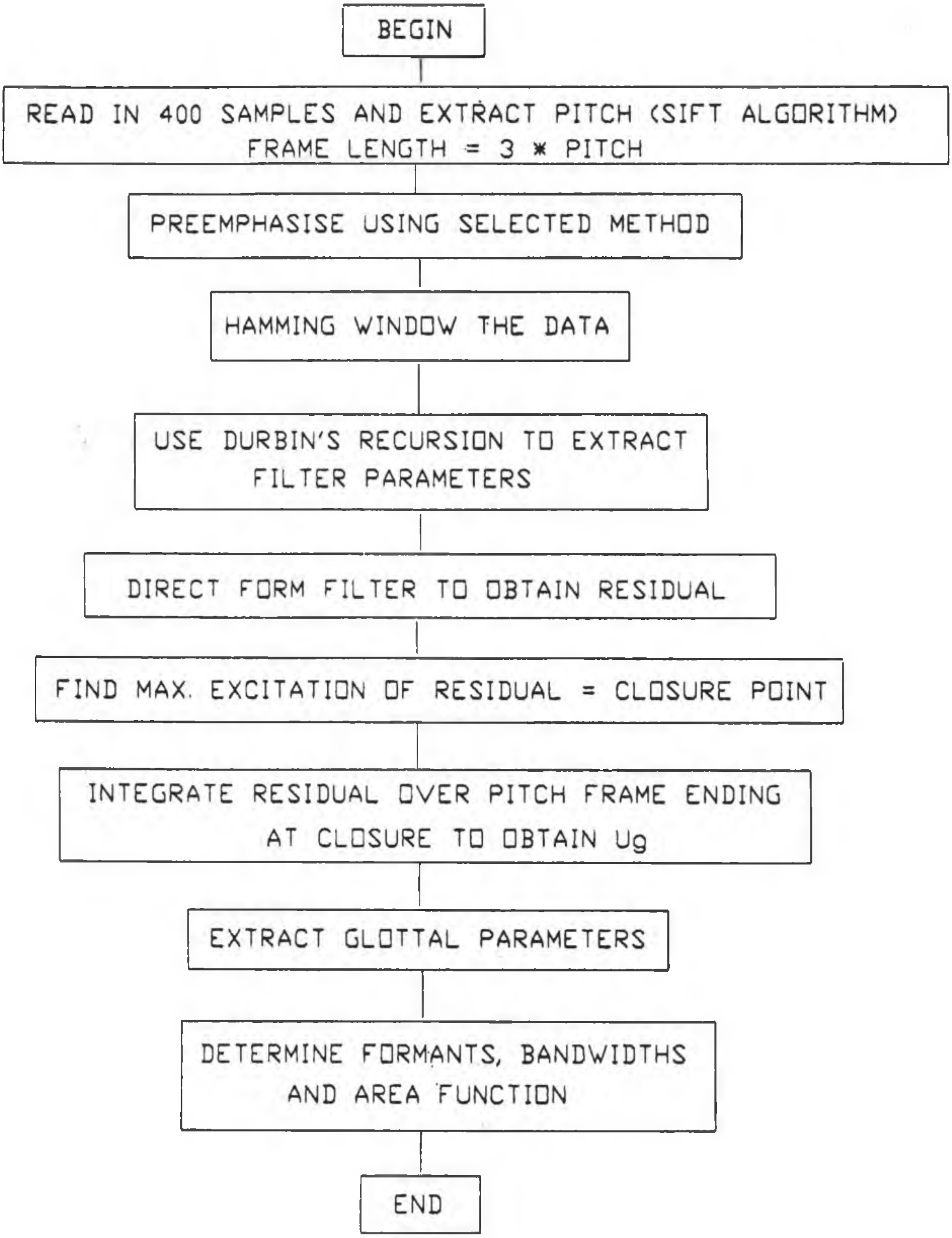

BEGIN
READ IN 400 SAMPLES AND EXTRACT PITCH (SIFT ALGORITHM)
FRAME LENGTH = 3 * PITCH
PREEMPHASISE USING SELECTED METHOD
HAMMING WINDOW THE DATA
USE DURBIN'S RECURSION TO EXTRACT FILTER PARAMETERS
DIRECT FORM FILTER TO OBTAIN RESIDUAL
FIND MAX. EXCITATION OF RESIDUAL = CLOSURE POINT
INTEGRATE RESIDUAL OVER PITCH FRAME ENDING AT CLOSURE TO OBTAIN Ug
EXTRACT GLOTTAL PARAMETERS
DETERMINE FORMANTS, BANDWIDTHS AND AREA FUNCTION
END

Fig 5.4 Algorithm for extracting V(z) using preemphasis

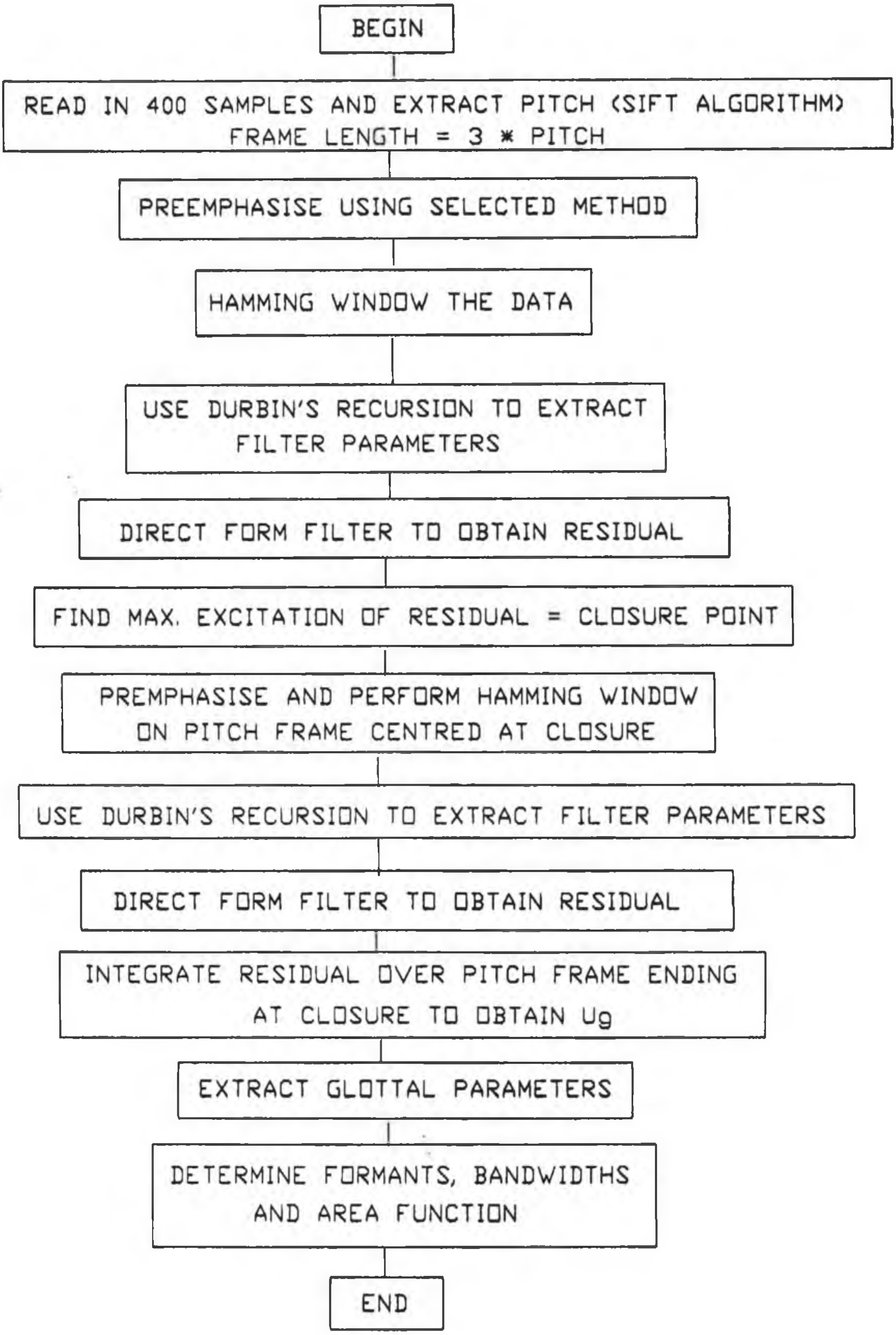

BEGIN
READ IN 400 SAMPLES AND EXTRACT PITCH (SIFT ALGORITHM)
FRAME LENGTH = 3 * PITCH
PREEMPHASISE USING SELECTED METHOD
HAMMING WINDOW THE DATA
USE DURBIN'S RECURSION TO EXTRACT FILTER PARAMETERS
DIRECT FORM FILTER TO OBTAIN RESIDUAL
FIND MAX. EXCITATION OF RESIDUAL = CLOSURE POINT
PREMPHASISE AND PERFORM HAMMING WINDOW ON PITCH FRAME CENTRED AT CLOSURE
USE DURBIN'S RECURSION TO EXTRACT FILTER PARAMETERS
DIRECT FORM FILTER TO OBTAIN RESIDUAL
INTEGRATE RESIDUAL OVER PITCH FRAME ENDING AT CLOSURE TO OBTAIN Ug
EXTRACT GLOTTAL PARAMETERS
DETERMINE FORMANTS, BANDWIDTHS AND AREA FUNCTION
END

Fig 5.5 Algorithm for pitch synchronous extraction of V(z)

5.3.2 Covariance over the Closed Glottis Interval

The basis of this method is that the glottis, as discussed in Chapter 2, closes for a significant portion of each pitch period.

Hence, for the model of Fig 5.1

$$u_G\ (n) = 0 \qquad (5.8)$$

over the closed glottis interval (CGI).

Defining the effective driving function Q(z) as

$$Q(z) \ = \ U_G\ (z)\ R(z) \qquad (5.9)$$

the speech production model is of the form :

$$s(n) = \sum_{k=0}^{M} a_k\ .\ s(n - k) + q(n) \qquad (5.10)$$

When the glottis closes, $u_G(n) = 0$, hence $q(n) = 0$, and

$$s(n) = \sum_{k=0}^{M} a_k\ .\ s(n - k) \qquad (5.11)$$

Thus one sample after closure, the waveform becomes a freely decaying oscillation (as in Prony's method). In practise there is an error term e(n), the total mean squared error defined as in the covariance method.

$$\alpha_M(n) \ = \sum_{j=n}^{n+N-M-1} e(j)^2 \qquad (5.12)$$

where e(n) and $\alpha_M(n)$ are theoretically zero for $n \geq L_c + 1$ and $n + N - M < L_o$. Usually, the normalized mean squared error $\eta(n)$ (NMSE) is used i.e.

$$\eta(n) \ = \ \frac{\alpha\ _M(n)}{\alpha_0\ (n)} \qquad (5.13)$$

where $\alpha_0(n)$ is the input signal energy. The NMSE for the vowel /a/ is shown in Fig 5.6.

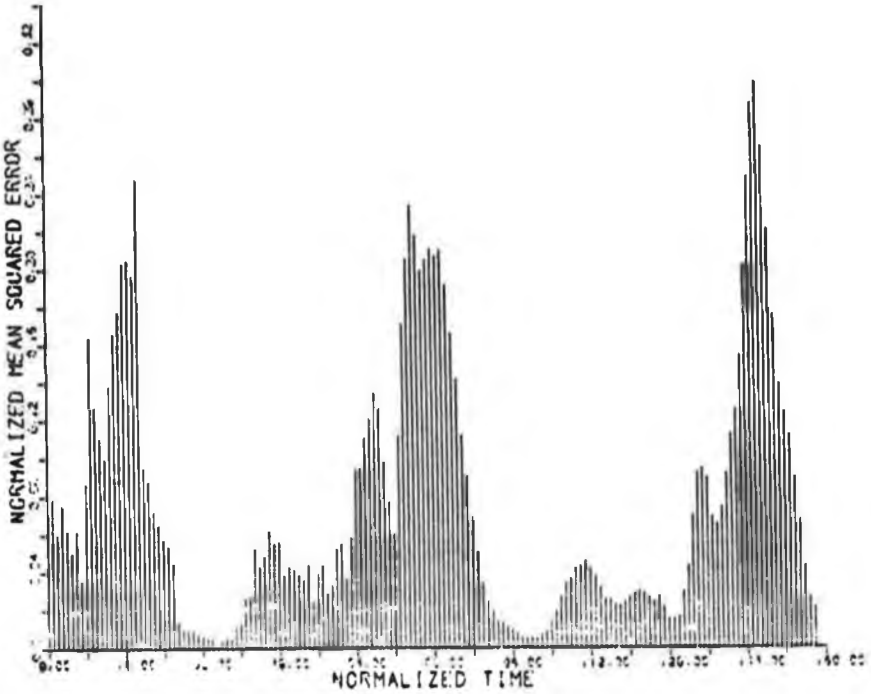


Fig 5.6 Normalized Mean Squared Error for the vowel /a/

5.3.2.1 Existing Methods for obtaining glottal closure

Two methods have been postulated which extract the instant of glottal closure, and hence the vocal tract filter over the CGI, using the NMSE. These are:

(i) Wong, Markel & Gray's method [32]

(ii) Strube's determinant method [33].

Both methods use the covariance method of analysis, performed sequentially over the analysis frame. However, they differ in their interpretation of the NMSE.

(i) If the glottis is assumed closed for

$$L_c + 1 \leqq n < L_0 \qquad (5.14)$$

then $q(n) = 0$ over this interval, with initial conditions taken from $s(L_c)$. In this method, the point of glottal closure is found by noting the first sample n_1 such that $\eta_M(n_1) = 0$, or in practise below a certain threshold, dependent on the minimum error. At the next sample n_2 where non - zero (or above threshold) error occurs, the opening location is defined as

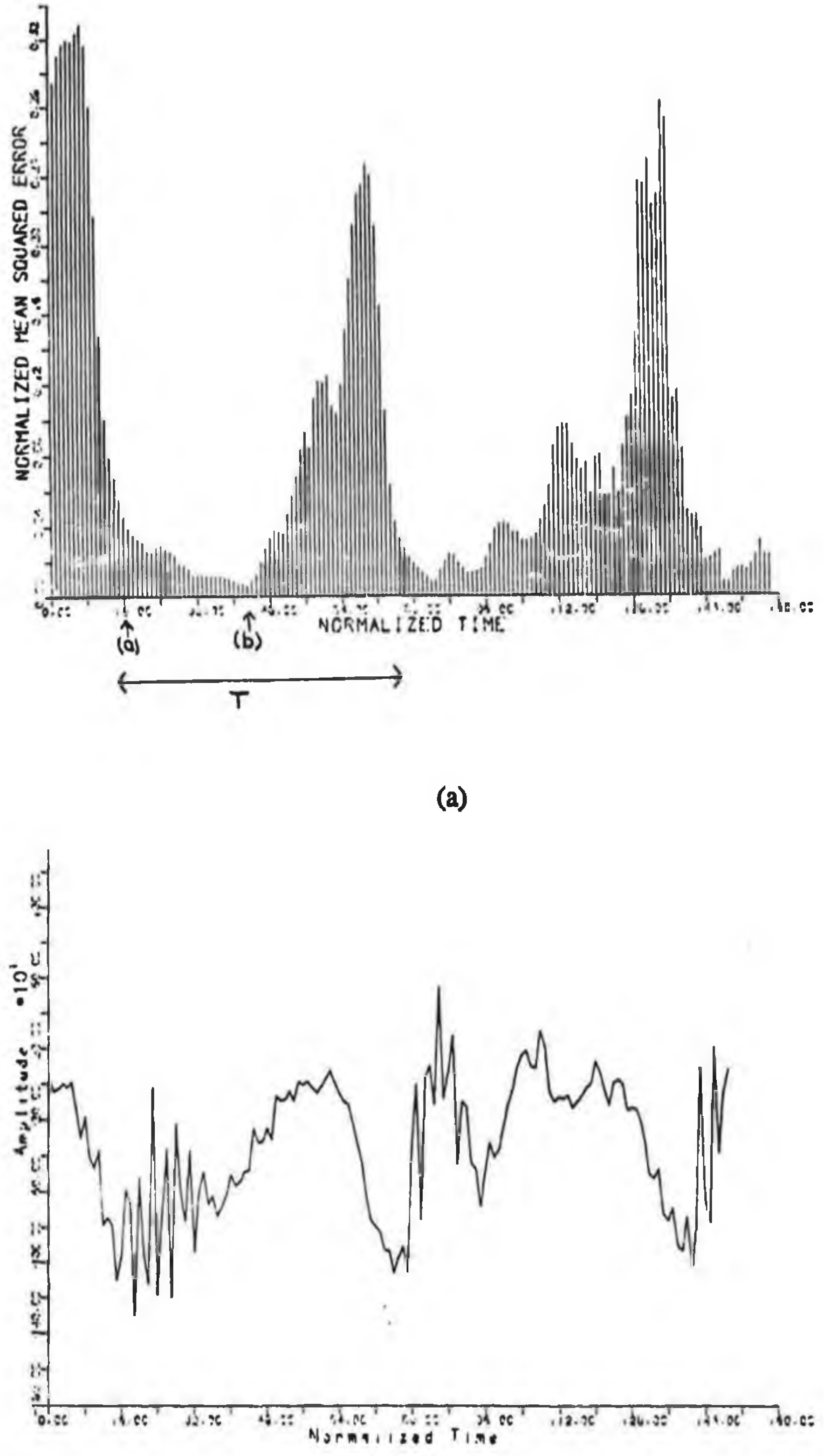
$$L_0 = n_2 + N - M - 1 \tag{5.15}$$

Normally the segment taken for obtaining V(z) is the place of minimum error in this interval.

(ii) Here, it is assumed that the vocal tract is most strongly excited at the instant of glottal closure. This instant should correspond to the highest increase in amplitude of the speech waveform, as the glottis closes far more abruptly than it opens. The prediction error will be large at this point, followed by good predictability, based on the speech being represented by freely decaying oscillations after closure. Thus for a segment which contains the glottal closure, the NMSE is maximum, after which it drops rapidly. This maximum corresponds to the maximum value of the Gram determinant [33], i.e the determinant of the covariance matrix over the chosen interval.

The above methods were tested for various vowels from two different speakers. A good indication of the accuracy of the transfer function obtained by any method is the quality of the glottal waveform obtained after filtering. If the correct transfer function has been extracted, the waveform should be smooth, contain no ripple due to formant remnants, and in shape and appearance generally approach an idealized glottal waveform, such as the one shown in Fig 5.3a. While the methods extracted good glottal waveforms in some instances, there were also cases where the methods failed.

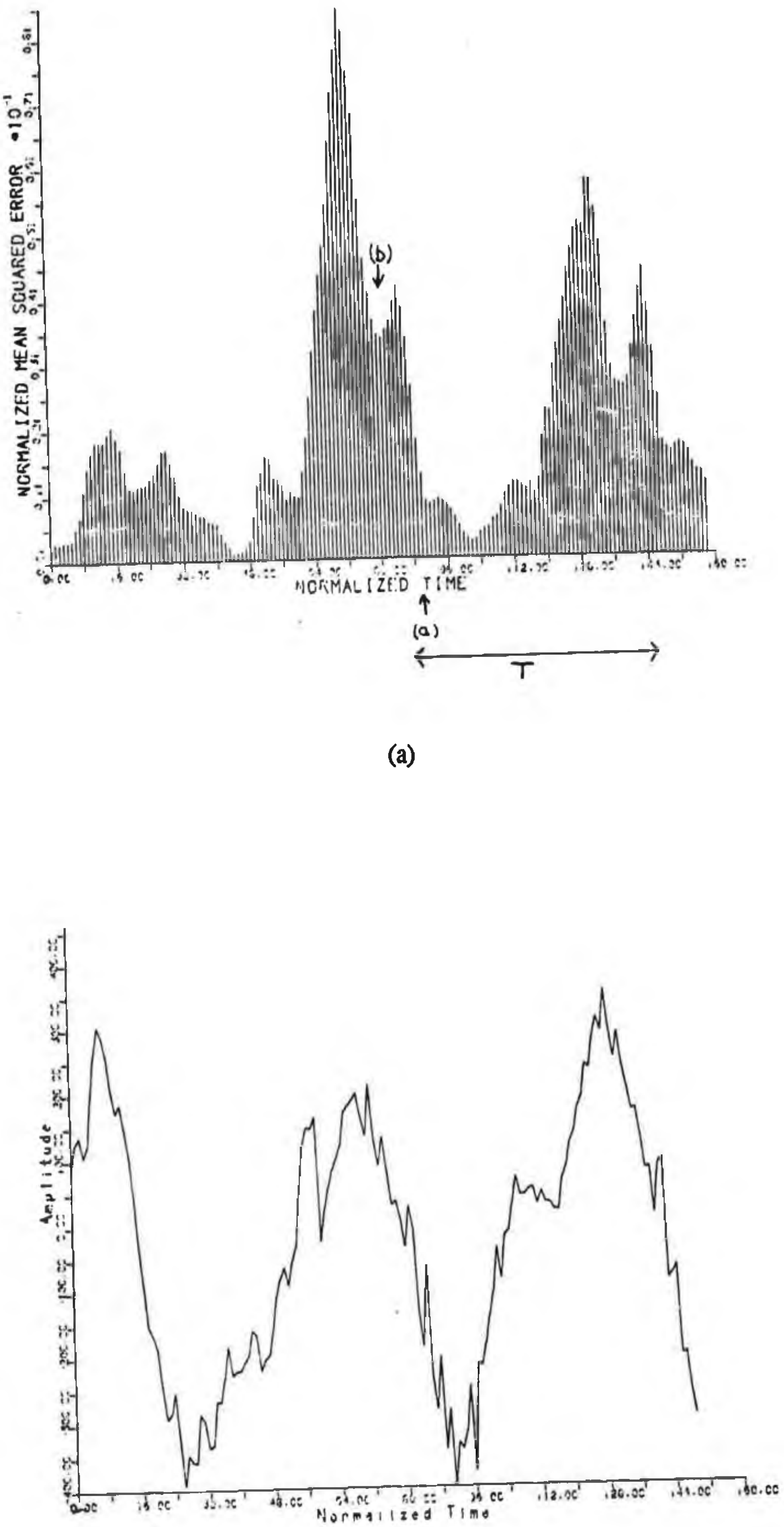
These are illustrated in Figs. 5.7 and 5.8. Fig 5.7a shows the NMSE graph for the vowel /er/ (T = pitch frame length). In this case, it can be seen that the minimum error occurs during the open phase (shown at (b)), nowhere near closure, which actually occurs shortly after the maximum drop (shown at (a)). So, using method (i), the corresponding glottal waveform for /er/, shown in Fig 5.7b,



(a)

(b)

Fig 5.7 (a) NMSE and (b) corresponding glottal waveform for the vowel /er/ obtained using Wong, Markel and Gray's Method



(a)

(b)

Fig 5.8 (a) NMSE and (b) corresponding glottal waveform for the vowel /u/ obtained using Strube's Method obtained by taking point (b) as the start of the CGI, is totally inaccurate.

Fig 5.8a shows the NMSE graph for the vowel /u/. In this case, from Fig 5.8a the maximum location occurs at the beginning of the open phase for /u/, (shown at (b)), and there are spurious drops which do not coincide with glottal closure (shown approximately at (a)). So, using method (ii), the glottal waveform for /u/, shown in Fig 5.8b, obtained by taking point (b) as the beginning of the CGI interval, is totally inaccurate.

It is obvious from the above that a method is required which takes into account both the minimum and maximum errors, and their relative positions. Neither of the above methods have discussed instability which often occurs for the covariance method. Methods have been proposed for stabilizing the covariance result [34]. However, it is accepted that the area function obtained after stabilization is meaningless, so doing this would be unacceptable for this research. A new method is proposed here, which starting with a reasonable estimate of closure location, extracts a very accurate stable vocal tract transfer function, and hence the area function.

5.3.2.2 Algorithm for extracting the Optimum Location

The flow chart for extracting the optimum location is shown in Fig 5.9. Because of the postitioning of the pitch analysis frame, the point of closure should be located in the first part of the frame. Initially the error range i.e. the maximum, η_{max} and minimum, η_{min} are obtained. From this the threshold value η_{th} is defined as

$$\eta_{th} = 2.0 * \eta_{min} \qquad (5.16)$$

First the general location of the maximum drop is obtained by finding the maximum of $\eta(n)$ - $\eta(n-5)$ in the first half of the frame, such that

$$\eta(n-5) \leq 1.5 * \eta_{th} \qquad (5.17)$$

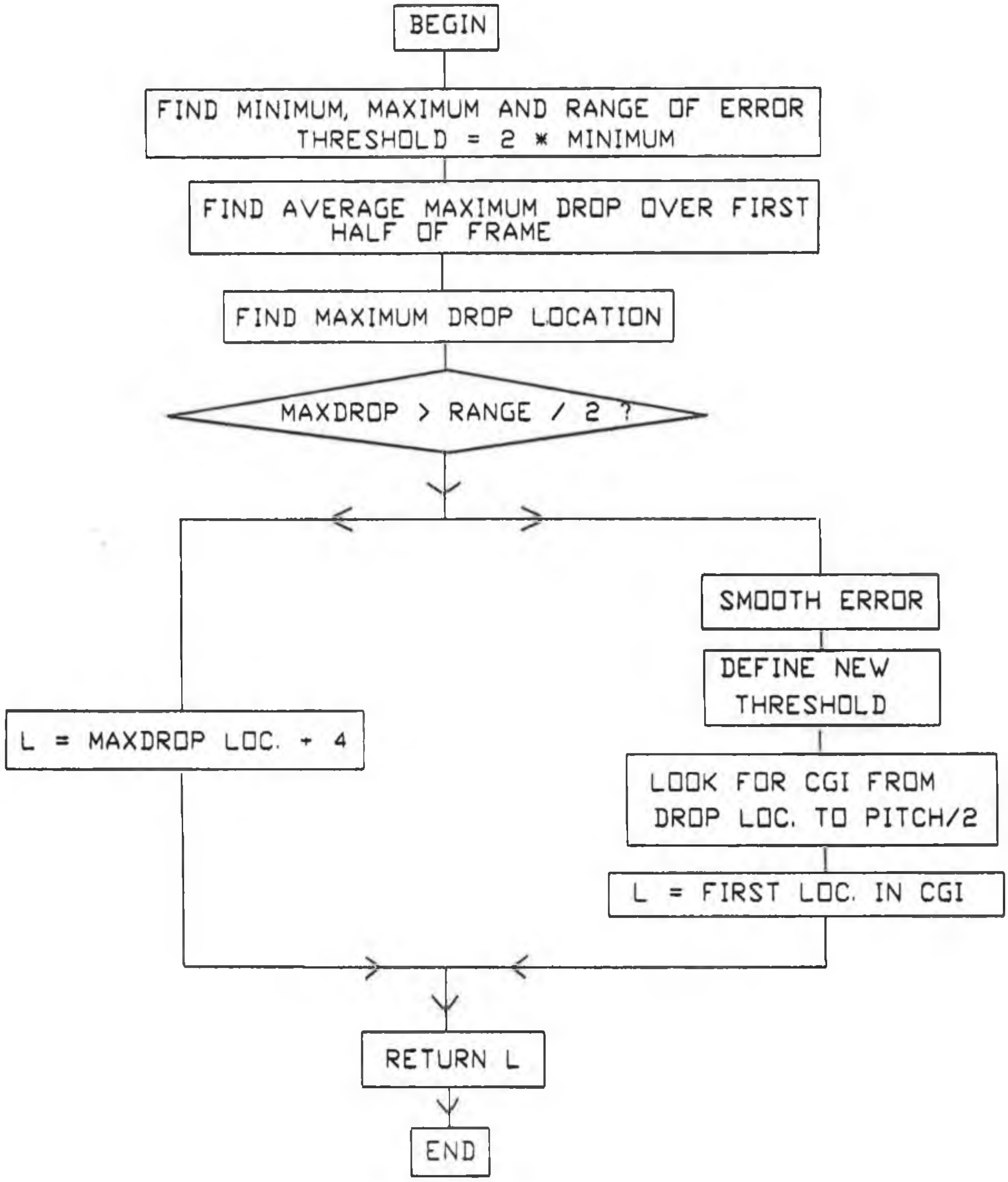

BEGIN
FIND MINIMUM, MAXIMUM AND RANGE OF ERROR
THRESHOLD = 2 * MINIMUM
FIND AVERAGE MAXIMUM DROP OVER FIRST HALF OF FRAME
FIND MAXIMUM DROP LOCATION
MAXDROP > RANGE / 2 ?
SMOOTH ERROR
DEFINE NEW THRESHOLD
L = MAXDROP LOC. + 4
LOOK FOR CGI FROM DROP LOC. TO PITCH/2
L = FIRST LOC. IN CGI
RETURN L
END

Fig 5.9 Algorithm for extracting glottal closure location

Once the general area is established, the maximum drop δ is searched for in the immediate location such that

$$\delta \geq \frac{(\eta_{max} - \eta_{min})}{1.5} \qquad (5.18a)$$

and

$$\eta(n) \leq 1.5 * \eta_{th} \qquad (5.18b)$$

just after the maximum. If this is clearly defined, the optimum location, L, is taken as

$$L = \delta + 4 \qquad (5.18c)$$

Taking four samples after is advisable, as there may be an oscillatory effect at exact closure [35]. Otherwise the error is smoothed in order to eliminate the effects of any spurious rises above the threshold in the CGI to be located. Starting at the first drop location found earlier, the first point to go below the threshold is found, according to method (i). The interval below the threshold must be at least M samples long, so the threshold may have to be increased slightly, or decreased if the interval seems too long e.g. corresponding to an open quotient ≥ 0.8, which would be extremely rare. The minimum error, as near to the beginning as possible, is chosen. This is to avoid the risk of entering the open region, which is quite possible for short closures and large analysis lengths, as is used in method (i). Including the open region would have a very detrimental effect on the formant frequencies extracted.

Usually such a comprehensive method results in a stable filter. However in cases where it does not, the immediate location is searched for appropriate filter coefficients.

5.3.2.3 Experimental Procedure

The flow chart of the analysis is shown in Fig 5.10. A block of speech is read in and its pitch determined using the SIFT algorithm [21]. The value of pitch is updated every third pitch frame. The approximate closure point is initially taken as the maximum excitation of the speech signal. By starting at twenty samples before this, the pitch frame used for analysing the NMSE will definitely include the full closed glottis interval (CGI). Starting at this location, the speech is

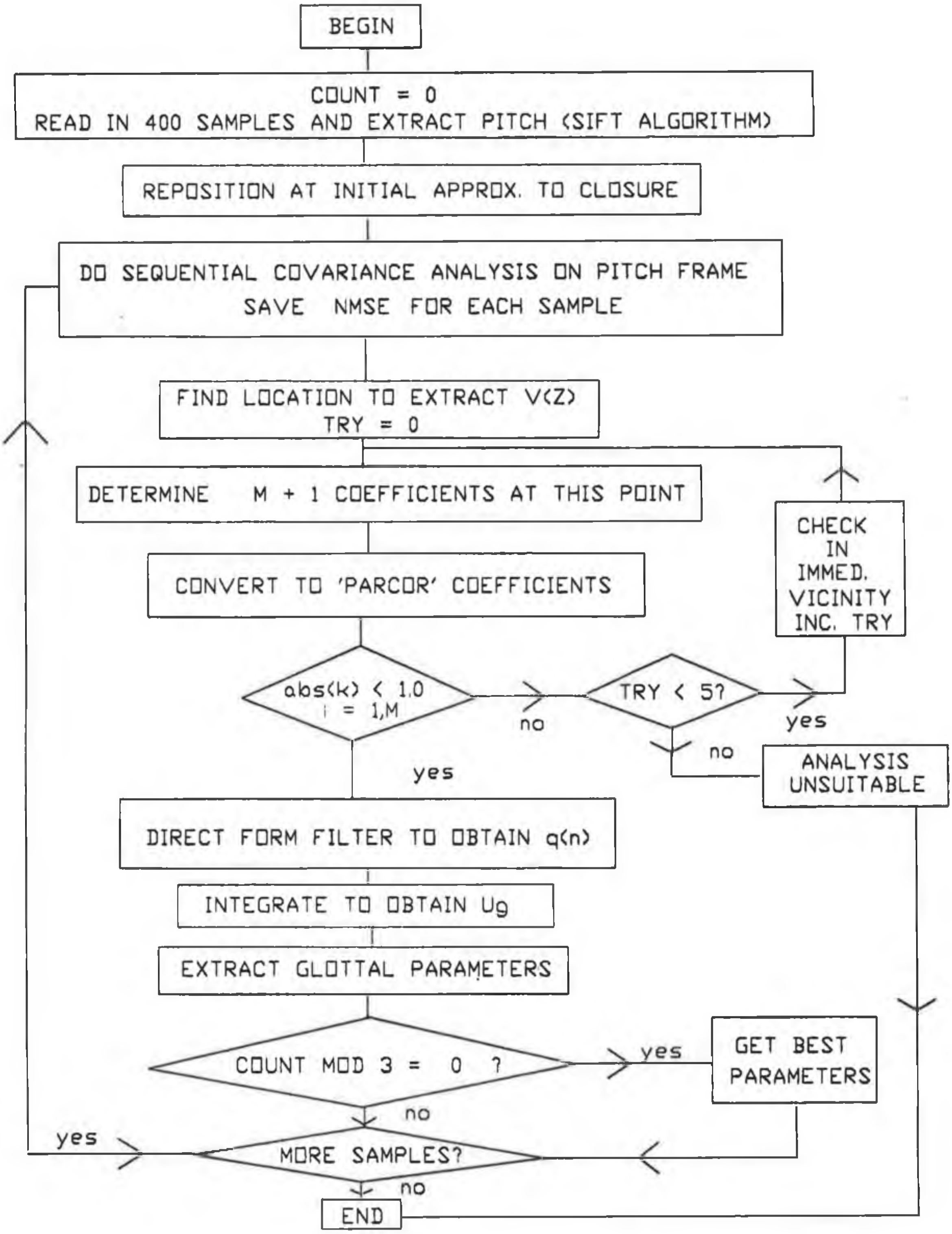

BEGIN
COUNT = 0
READ IN 400 SAMPLES AND EXTRACT PITCH (SIFT ALGORITHM)
REPOSITION AT INITIAL APPROX. TO CLOSURE
DO SEQUENTIAL COVARIANCE ANALYSIS ON PITCH FRAME
SAVE NMSE FOR EACH SAMPLE
FIND LOCATION TO EXTRACT V(Z)
TRY = 0
DETERMINE M + 1 COEFFICIENTS AT THIS POINT
CHECK IN IMMED. VICINITY INC. TRY
CONVERT TO 'PARCOR' COEFFICIENTS
abs(k) < 1.0
i = 1,M
no
TRY < 5?
yes
no
ANALYSIS UNSUITABLE
yes
DIRECT FORM FILTER TO OBTAIN q(n)
INTEGRATE TO OBTAIN Ug
EXTRACT GLOTTAL PARAMETERS
COUNT MOD 3 = 0 ?
yes
GET BEST PARAMETERS
no
yes
MORE SAMPLES?
no
END

Fig 5.10 Algorithm for extracting V(z) using CGI analysis

preemphasised and sequential covariance analysis, using Cholesky decomposition, is carried out. Preemphasis is used because it makes the drop in the NMSE more pronounced. An interval of length N=22 is taken, with the order of analysis M=8. Computation is saved by noting that each time a new covariance matrix is required, only one new row is added, as only one sample is being advanced at a time. The NMSE from each sample is saved in an array. At the end of the pitch frame, this array is analysed to extract the location from which to determine V(z).

For the chosen location, the LPC coefficients are determined, and the corresponding filter stability is tested by obtaining the corresponding reflection coefficients, according to eqn. (4.41), and checking for stability according to eqn. (4.26). An alternative location in the immediate area is chosen, if necessary. Often, by examining the stability of each location, long regions of stability may be found, and this may be a good alternative indication of the closure region. However, the additional computation does not deem it worthwhile, unless absolutely necessary.

The residual (error) signal q(n) is now obtained by passing the unpreemphasised speech through the inverse filter V(z). In order to extract the glottal waveform and corresponding parameters, an interval of at least two pitch periods is used. The glottal waveform over an interval of a pitch period is obtained by integrating q(n), such that a full glottal pulse is included i.e. the interval begins just before opening, ending after closure. This simplifies extraction of the glottal parameters.

Three frames are analysed at a time, and the frame with the most realistic parameters is used to code the speech. To decide which frame to use, the formants, bandwidths and area functions are compared for the three cases. Frames with abnormally large bandwidths, or unstable filters are discarded immediately. Of the remaining, the one with the most realistic looking area function is extracted, for example, an area function may have a large range (extreme values) due to the small bandwidths extracted. If necessary, to ensure continuity between frames, and reasonable vocal tract shapes, the bandwidths may be systematically damped e.g. by 50Hz, i.e. a corresponding change in the filter parameters of

$$a_i' = a_i \exp(-50i\Pi T) \qquad (5.19)$$

where T is the sampling rate, as suggested by Mallawany [36]. In fact much research in formant analysis in the past has used default values for bandwidths [12], so this is not unreasonable. In order to ensure continuity and stability, Mallawany suggested using a special Hamming window on the covariance analysis frame. However, when this was tried, it resulted in a total smearing of the formants obtained. This was to be expected, as the advantages of the covariance method (i.e. no need for windowing) was destroyed, making its accuracy no better, and probably worse than the autocorrelation method.

5.4 Extraction of Glottal Parameters

The algorithm for extracting the glottal parameters, as defined in Section 2.4.2, is shown in Fig 5.11. A robust, reliable algorithm for extracting these parameters is required, particularly in the case of the glottal waveform obtained from autocorrelation methods, as it may contain undesirable ripple. For this reason, the glottal waveform is smoothed before examination.

The peak value, which separates opening and closing portions, is first found, as it is always the most reliable point in the waveform. The closure point is found by the cessation of negative slope to the right of the peak, or else by the pitch period end, whichever comes first. This second clause is required, particularly in the case of an autocorrelation derived waveform, as sometimes the negative slope continues beyond closure. The opening location, which can be more difficult to locate, is obtained by going left of the peak in the same manner. Bumps in the waveform (due to formant ripple) are ignored if the amplitude between the peak

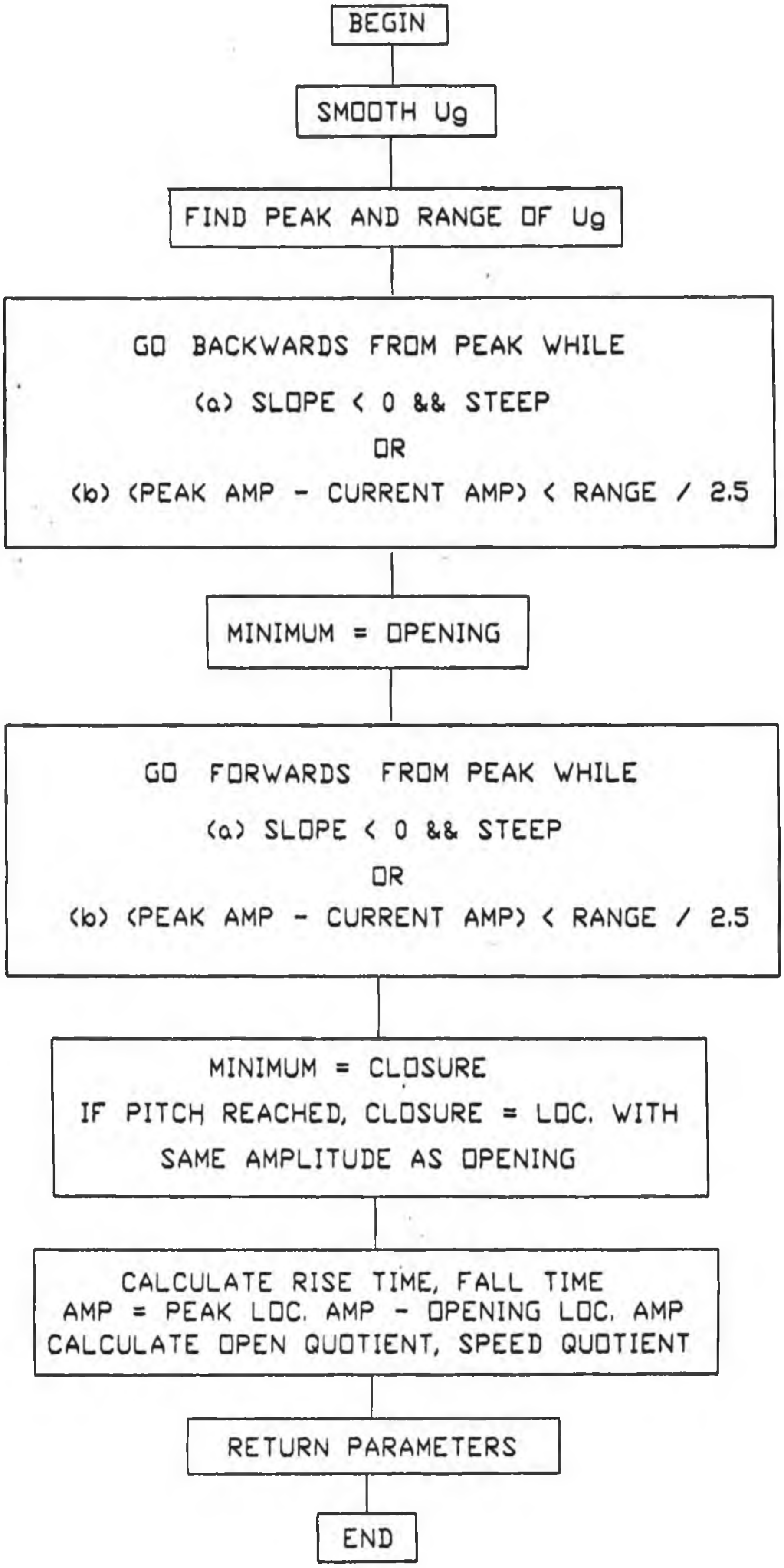

BEGIN
SMOOTH Ug
FIND PEAK AND RANGE OF Ug
GO BACKWARDS FROM PEAK WHILE
(a) SLOPE < 0 && STEEP
OR
(b) (PEAK AMP - CURRENT AMP) < RANGE / 2.5
MINIMUM = OPENING
GO FORWARDS FROM PEAK WHILE
(a) SLOPE < 0 && STEEP
OR
(b) (PEAK AMP - CURRENT AMP) < RANGE / 2.5
MINIMUM = CLOSURE
IF PITCH REACHED, CLOSURE = LOC. WITH
SAME AMPLITUDE AS OPENING
CALCULATE RISE TIME, FALL TIME
AMP = PEAK LOC. AMP - OPENING LOC. AMP
CALCULATE OPEN QUOTIENT, SPEED QUOTIENT
RETURN PARAMETERS
END

Fig 5.11 Algorithm for extracting glottal parameters

location and the current location is less than the overall range of the signal divided by 2.5. This value was found to be appropriate from visual examination of signals.

Once these three locations are determined, the glottal parameters are easily extracted. The closure location is used to determine the amplitude of the glottal pulse.

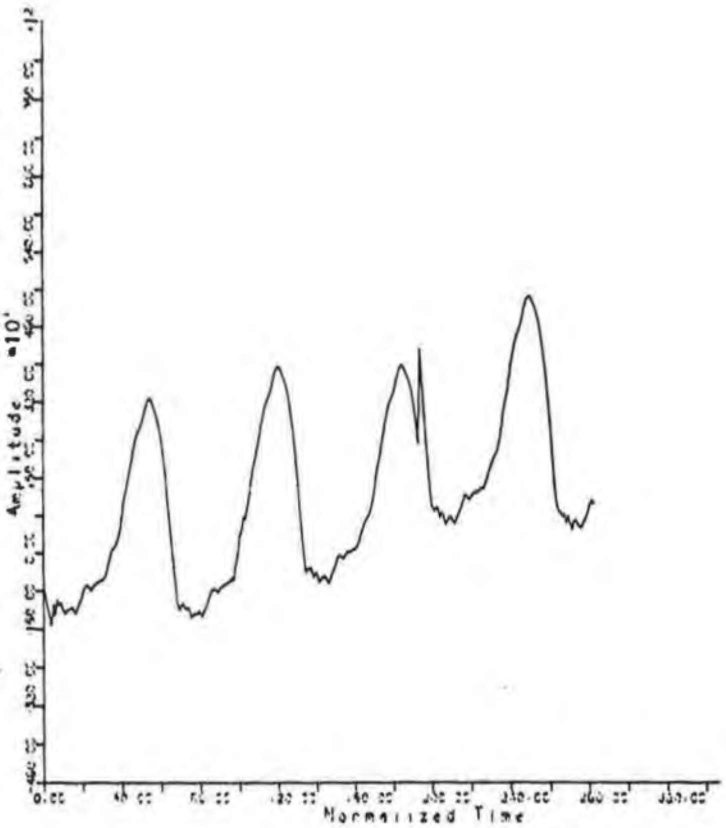
5.5 Experimental Results and Conclusions

In this section, a comparison of the waveforms obtained from each autocorrelation-based method is carried out, and then the best of these, the first-order preemphasis method is compared to the covariance derived analysis method. This is followed by a general discussion and explanation of results obtained.

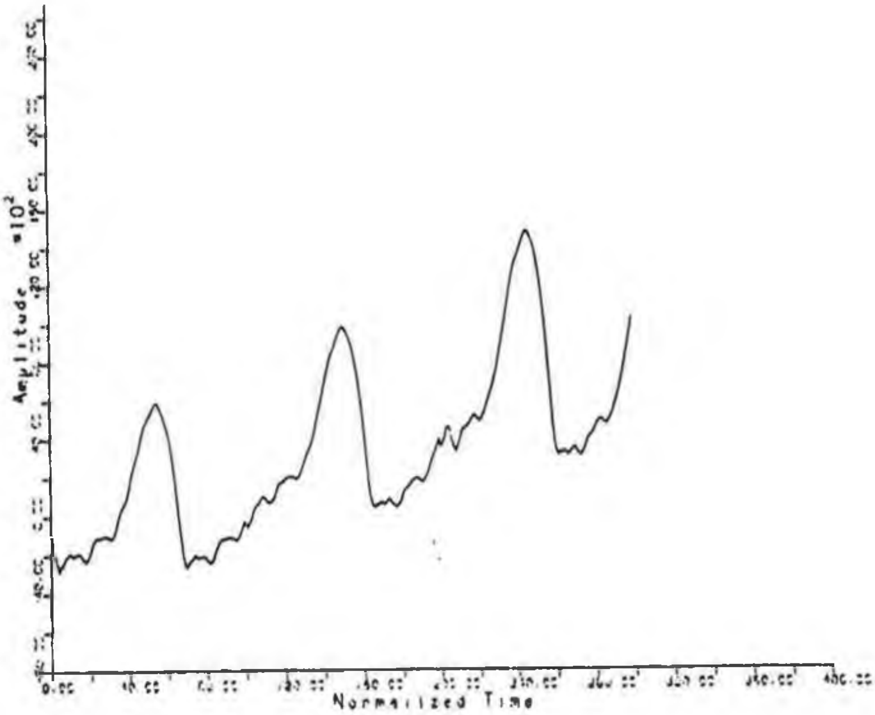
5.5.1 Comparison of Preemphasis Methods

The glottal waveforms obtained for each inverse filtering method for the vowels /a/ and /er/ are shown in Fig 5.12 and 5.13. These waveforms are consistent with the general trend of results obtained from all the vowels analysed. The most consistent results for the vast majority of vowels are obtained using first order preemphasis. It appears that the other methods use too much preemphasis, which is as bad as too little [37].

While good results for the adaptive multi-stage method are reported for Japanese vowels, it does not work well for English vowels. For the vowel /er/, it yields reasonable looking waveforms, however in general the results were similar to that for the vowel /a/. A filter whose coefficients are based on the incoming signal should detect when less preemphasis is required, so in the majority of cases, the method is not much use. Similar results are obtained for the first order adaptive

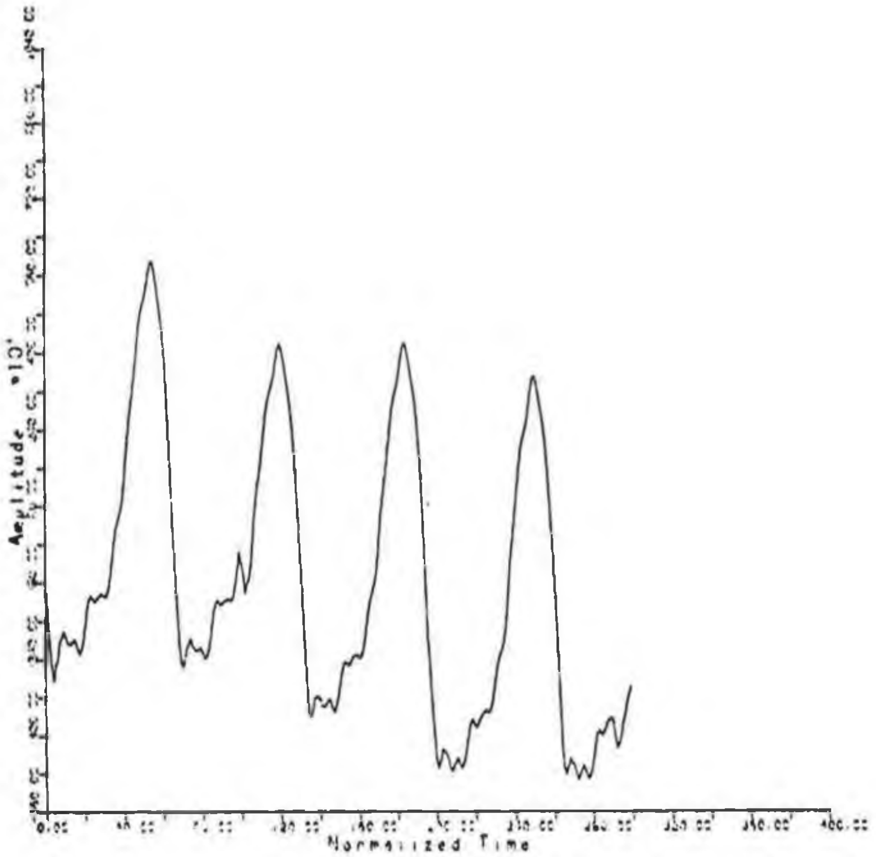


(a) First Order Preemphasis

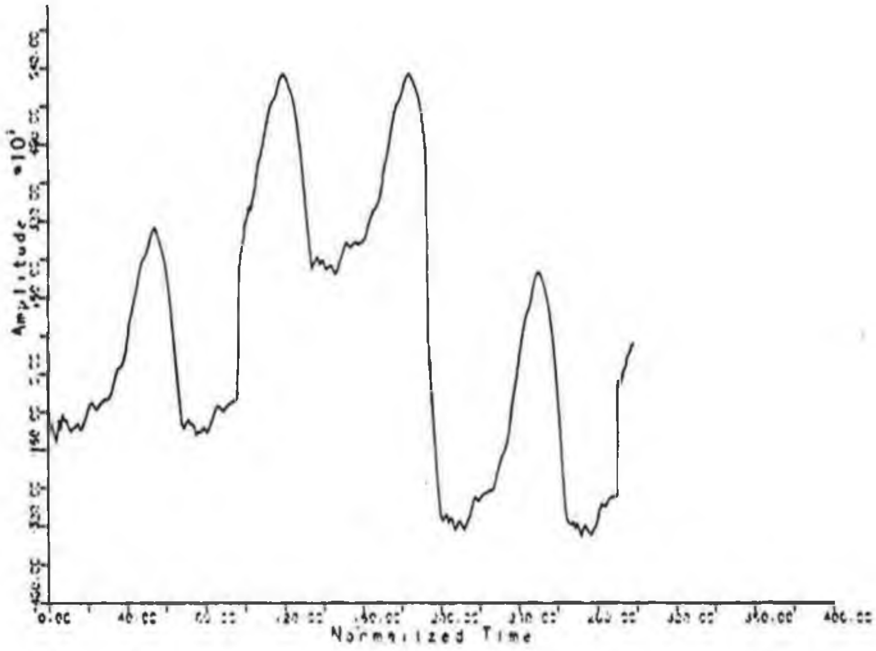


(b) Adaptive First Order Preemphasis

5.12 Glottal Waveforms obtained for the vowel /a/ using preemphasis methods

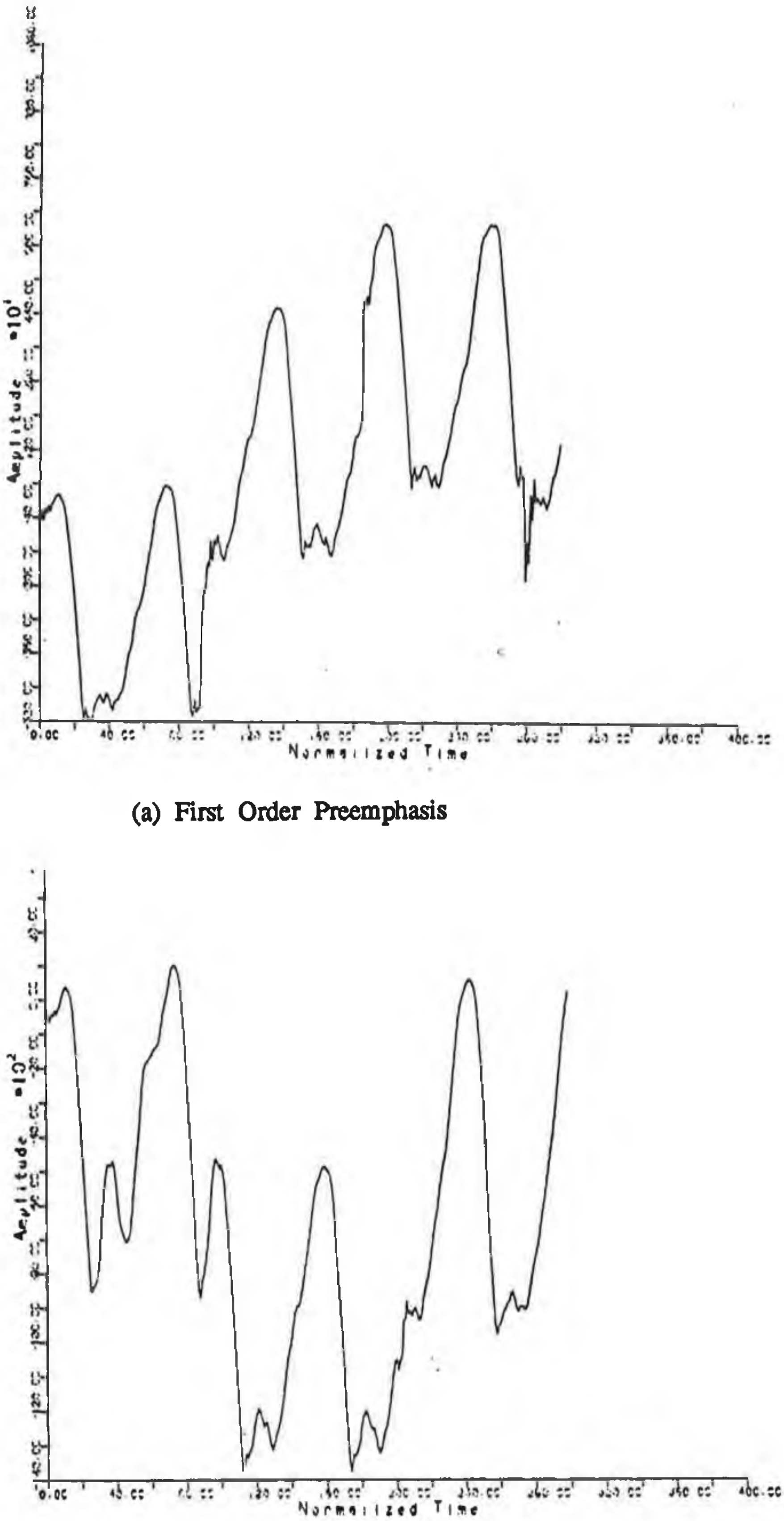


(c) Adaptive Multi Order Preemphasis



(d) Pitch Synchronous with First Order Preemphasis

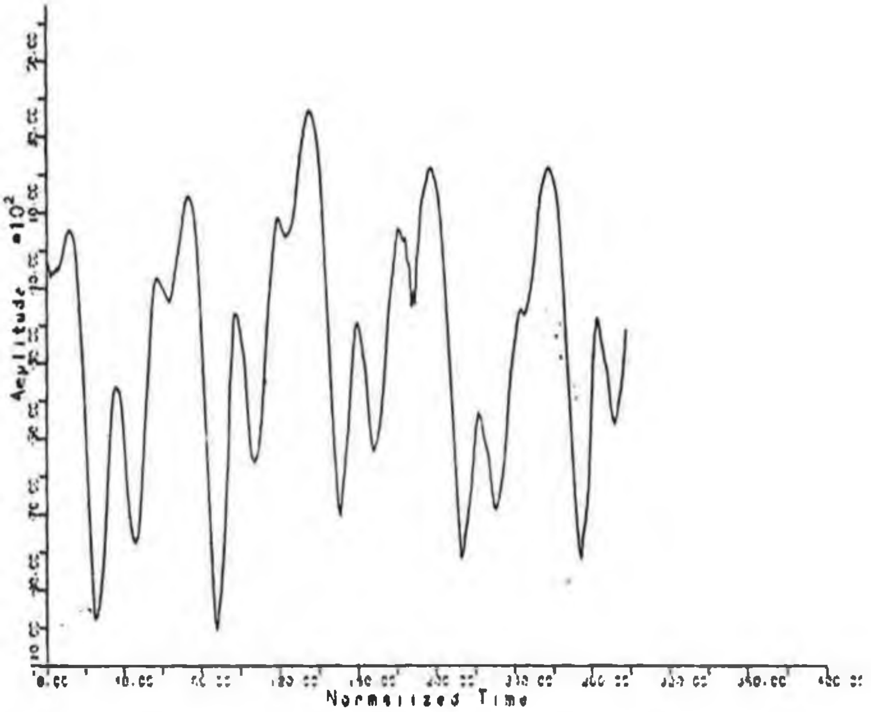
5.12 Glottal Waveforms obtained for the vowel /a/ using preemphasis methods



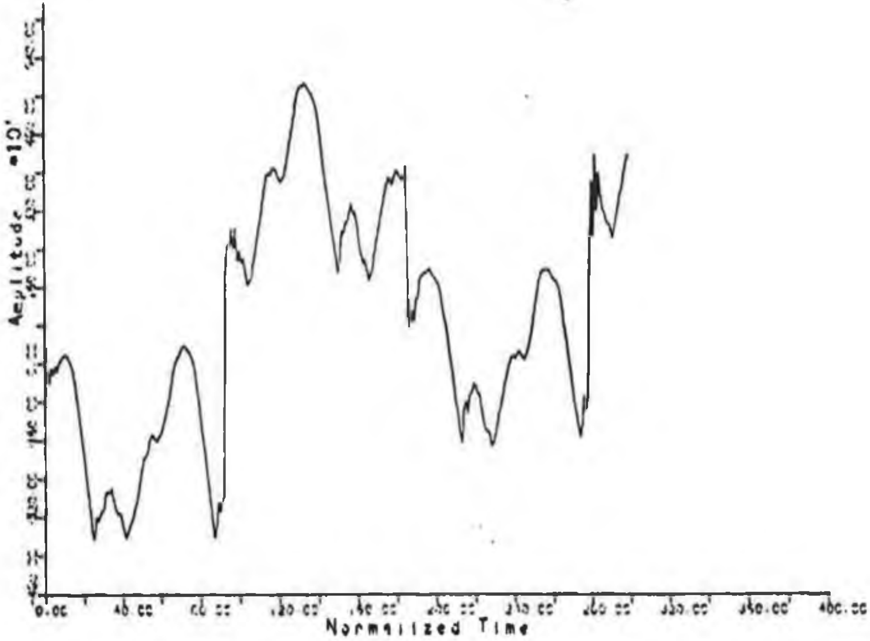
(a) First Order Preemphasis

(b) Adaptive First Order Preemphasis

5.13 Glottal Waveforms obtained for the vowel /er/ using preemphasis methods



(c) Adaptive Multi Order Preemphasis



(d) Pitch Synchronous with First Order Preemphasis

5.13 Glottal Waveforms obtained for the vowel /er/ using preemphasis methods method, in this case it works well for /a/ but not for /er/.

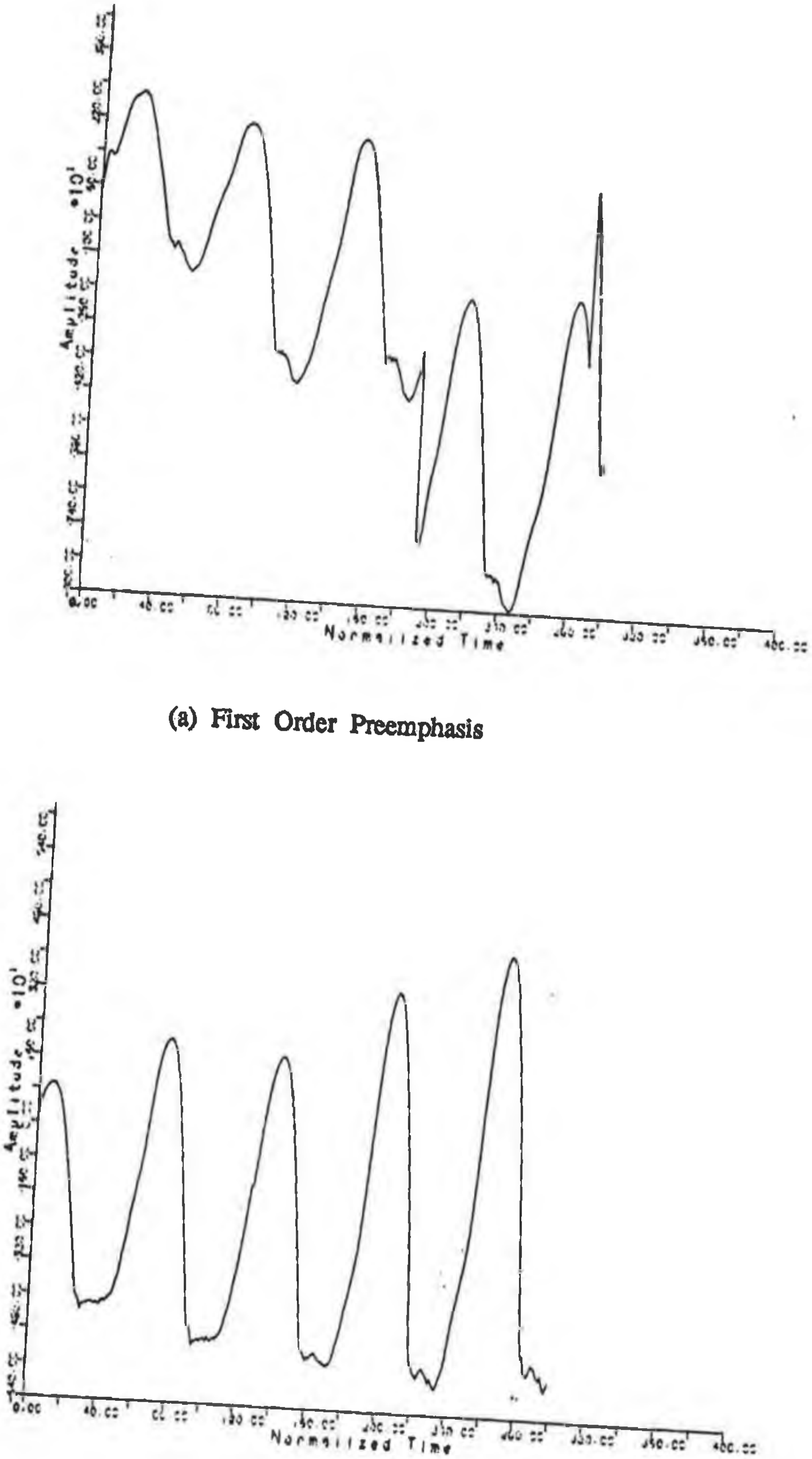
In the case of the pitch synchronous method, the results were also inconsistent. This may be attributed to the difficulty of defining glottal closure and opening, the former from the residual, and the latter from the resulting glottal waveform. Using iteration to improve the waveform, as suggested by Hedelin [38], actually worsens the situation, due to the lack of a very accurate starting estimate. In cases where the open quotient is high, the interval for analysis should be a lot less than a pitch period to avoid the open region as discussed earlier, which is not recommended for the autocorrelation method.

Thus, ordinary preemphasis, despite its discontinuities and occasional erratic behaviour, is the preferred inverse filtering method. It will be compared to the CGI method in the next section.

5.5.2 Comparison of CGI and first order preemphasis methods

The glottal waveforms obtained for the two methods are shown in Fig 5.14 - 5.17 for the vowels /u/, /ae/, /ah/ and /uh/. It is immediately obvious that in all cases the waveforms obtained from CGI analysis are superior, containing far less (if any) formant ripple. Generally the waveforms obtained from CGI analysis are of a high standard. In some cases, reasonable waveforms are obtained from both methods, and a comparison of the properties of the transfer function obtained from both methods is advisable.

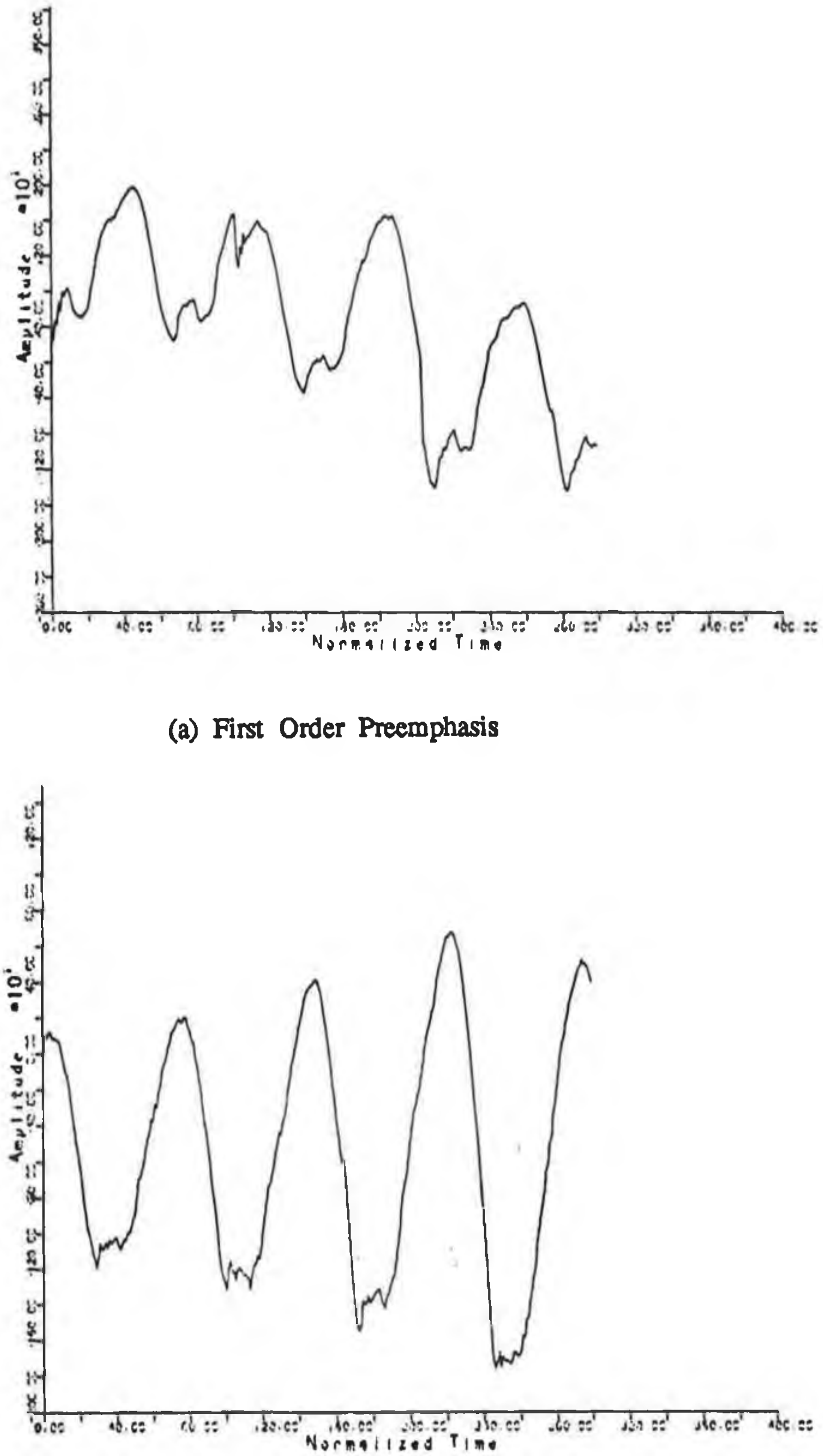
The area functions and corresponding bandwidths obtained for both methods for a wide cross-section of vowels are shown in Fig 5.18 - 5.24. In most cases, the area profiles obtained from both methods are quite similar, differing in finer details. It is noted that formant bandwidths are in general far greater for the autocorrelation method. First formants are reasonably close in both cases, with the percentage error greater for the higher formants.



(a) First Order Preemphasis

(b) CGI analysis

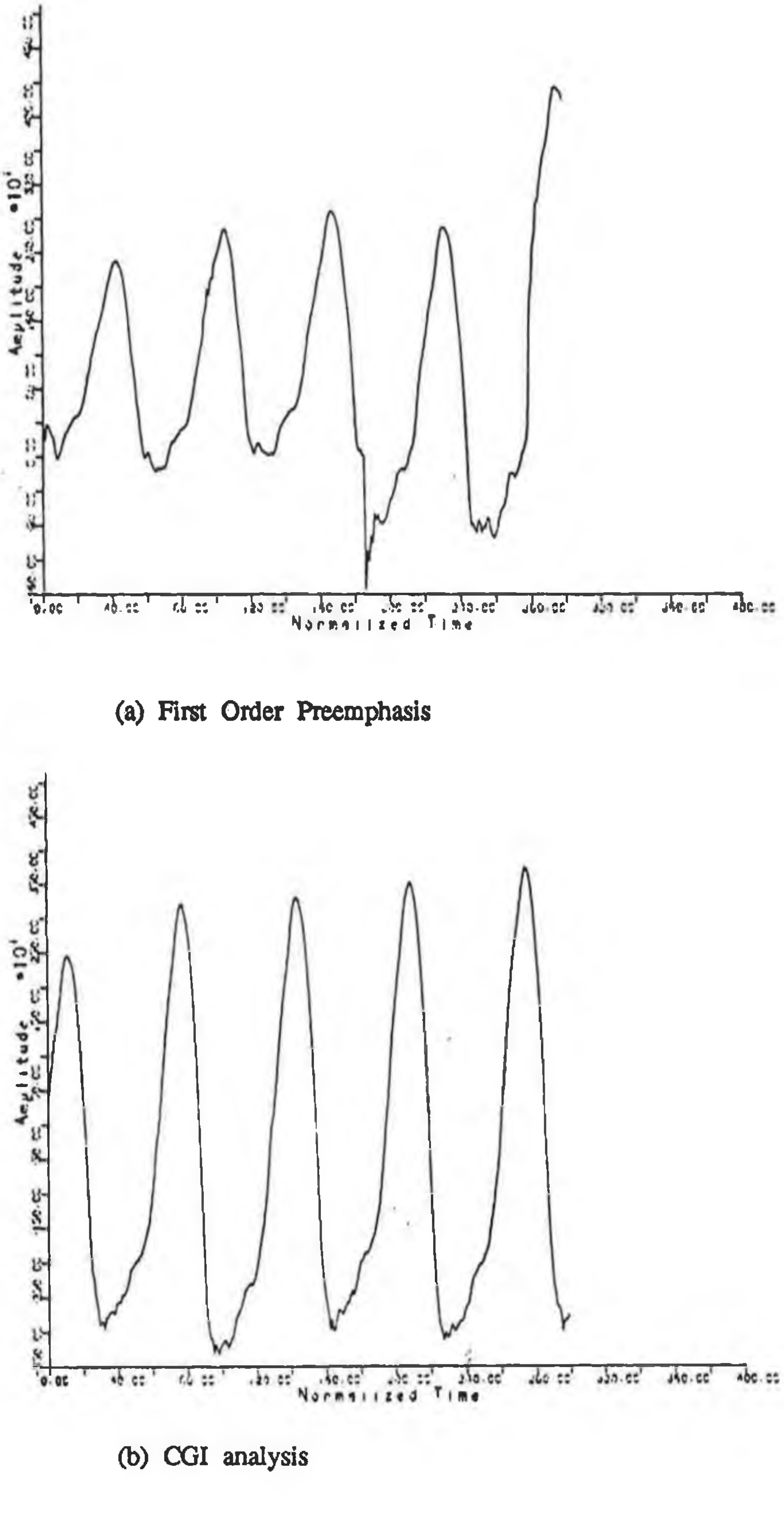
5.14 Glottal Waveforms obtained for the vowel /u/



(a) First Order Preemphasis

(b) CGI analysis

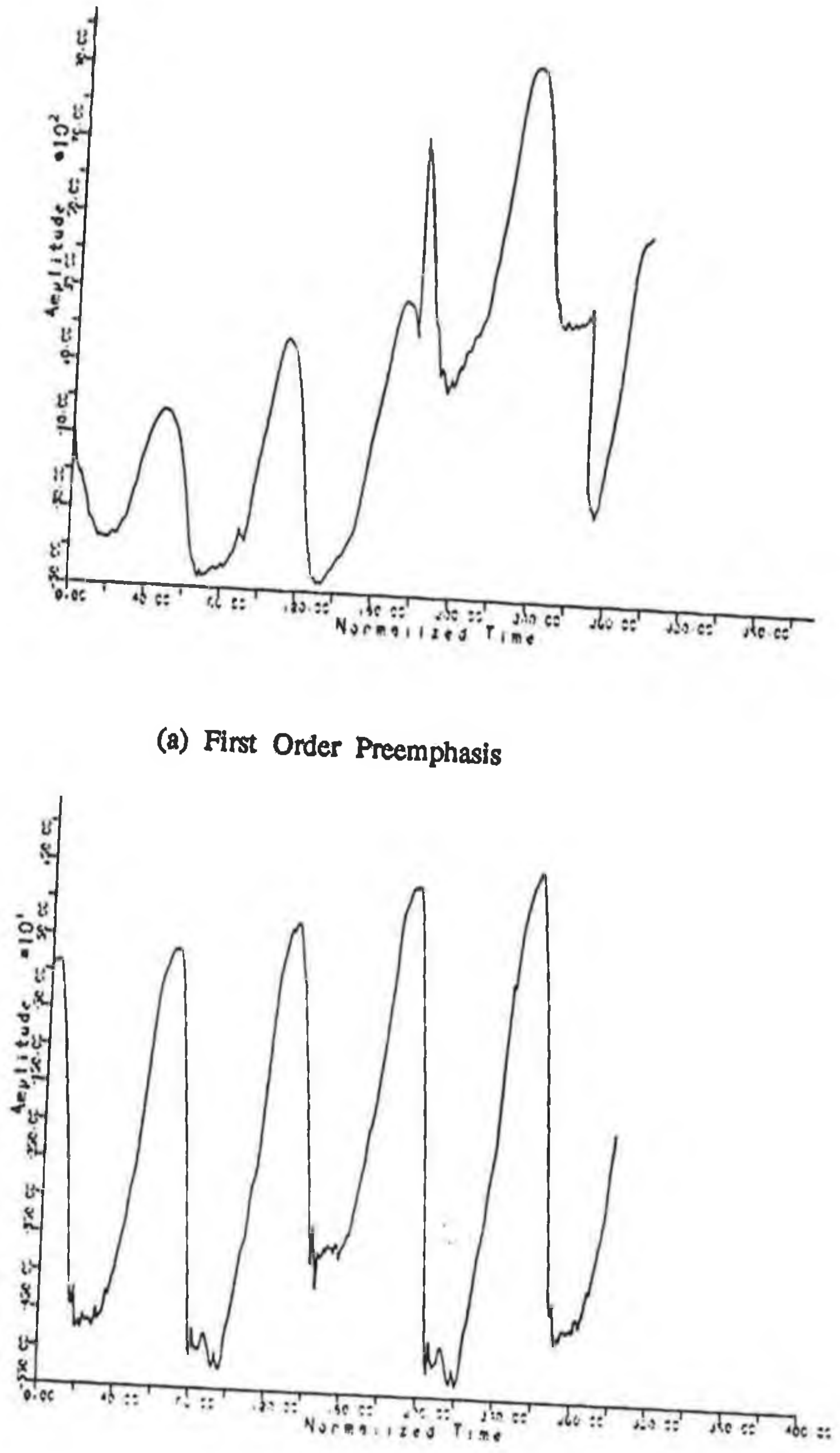
5.15 Glottal Waveforms obtained for the vowel /ae/



(a) First Order Preemphasis

(b) CGI analysis

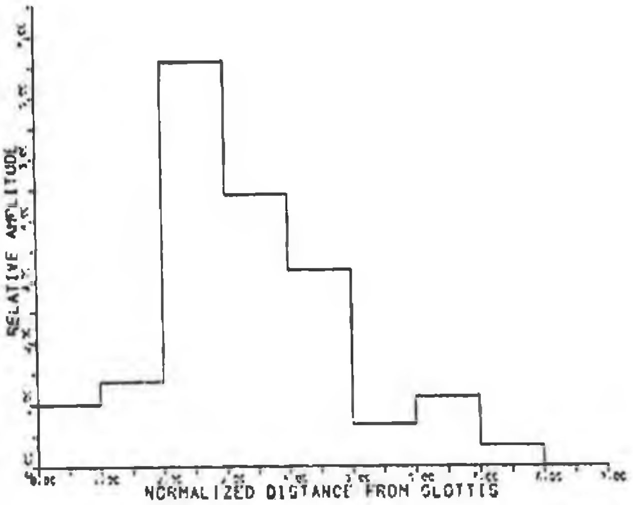
5.16 Glottal Waveforms obtained for the vowel /ah/



(a) First Order Preemphasis

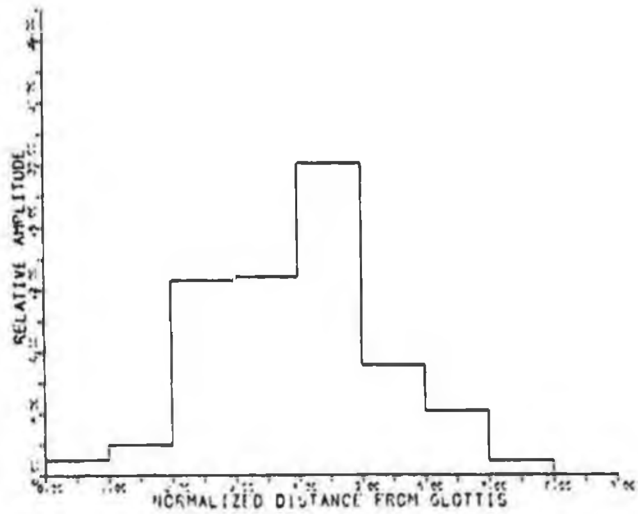
(b) CGI analysis

5.17 Glottal Waveforms obtained for the vowel /uh/



	1	2	3	4	
F	254	1795	2215	3004	Hz
B	44	108	440	153	Hz

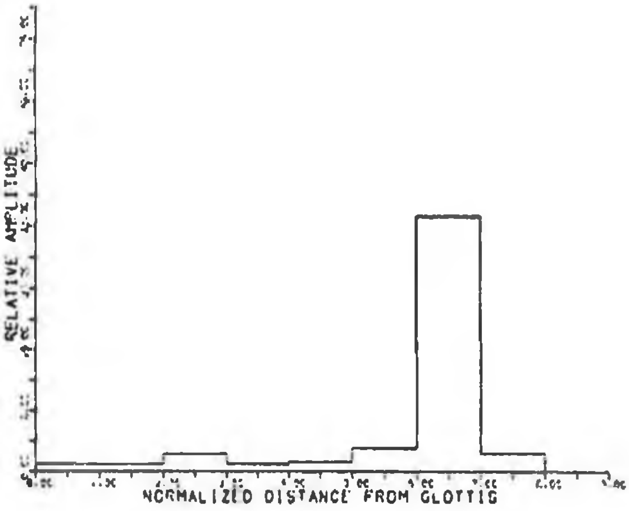
(a) CGI method



	1	2	3	4	
F	272	1898	2542	3072	Hz
B	18	184	622	191	Hz

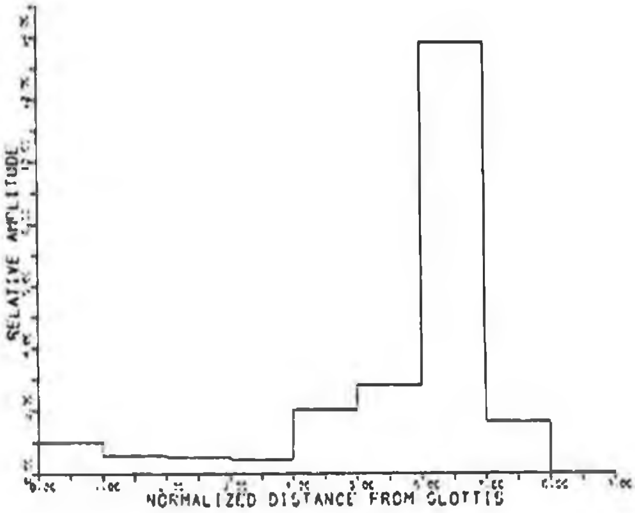
(b) First order Preemphasis method

Fig 5.18 Area Functions, Formants and Bandwidths for vowel /i/



	1	2	3	4	
F	497	749	2000	2869	Hz
B	188	322	495	250	Hz

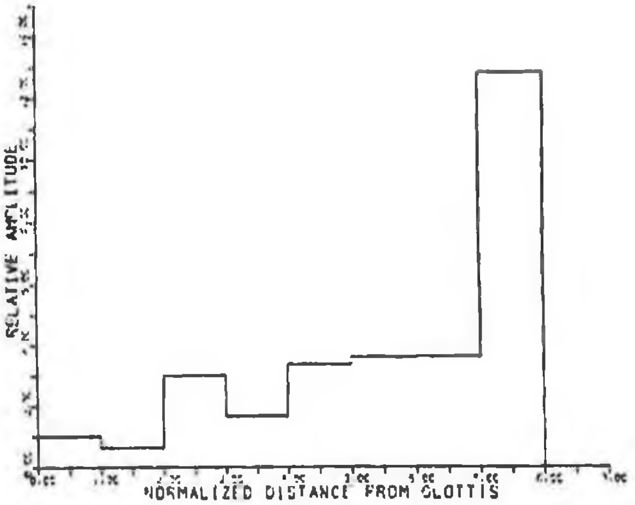
(a) CGI method



	1	2	3	4	
F	666	799	2542	3072	Hz
B	301	258	134	232	Hz

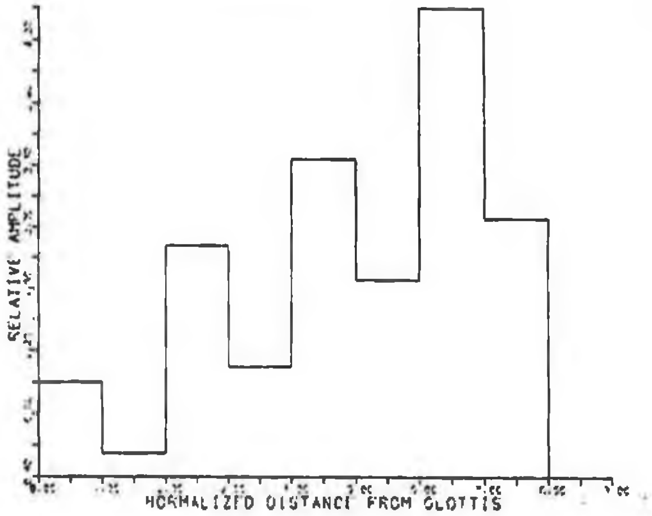
(b) First order Preemphasis method

Fig 5.19 Area Functions, Formants and Bandwidths for vowel /ah/



	1	2	3	4	
F	601	1199	1953	2870	Hz
B	70	173	345	44	Hz

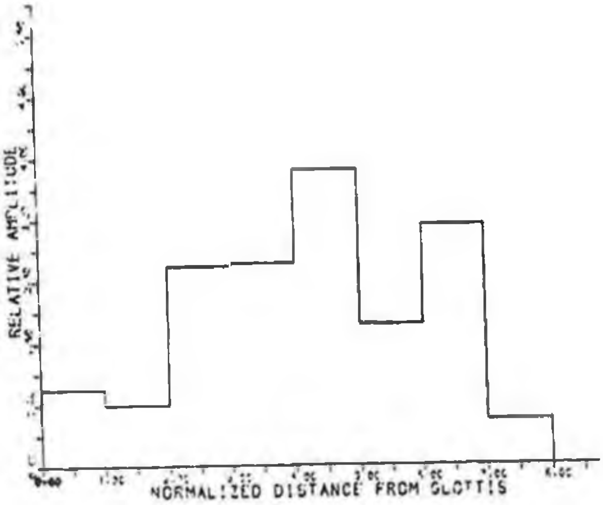
(a) CGI method



	1	2	3	4	
F	646	1399	2056	2873	Hz
B	306	600	375	83	Hz

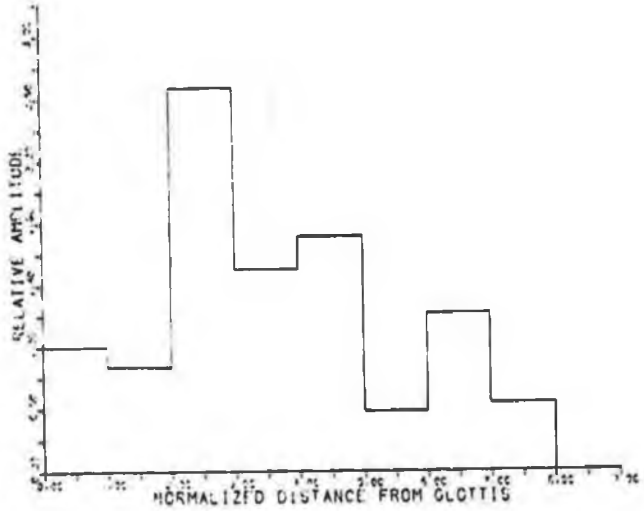
(b) First order Preemphasis method

Fig 5.20 Area Functions, Formants and Bandwidths for vowel /uh/



	1	2	3	4	
F	405	1441	2063	3021	Hz
B	54	244	212	97	Hz

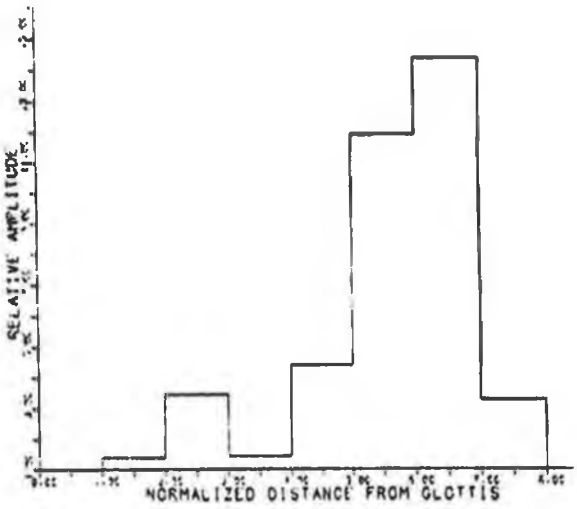
(a) CGI method



	1	2	3	4	
F	396	1648	2149	2905	Hz
B	134	302	340	156	Hz

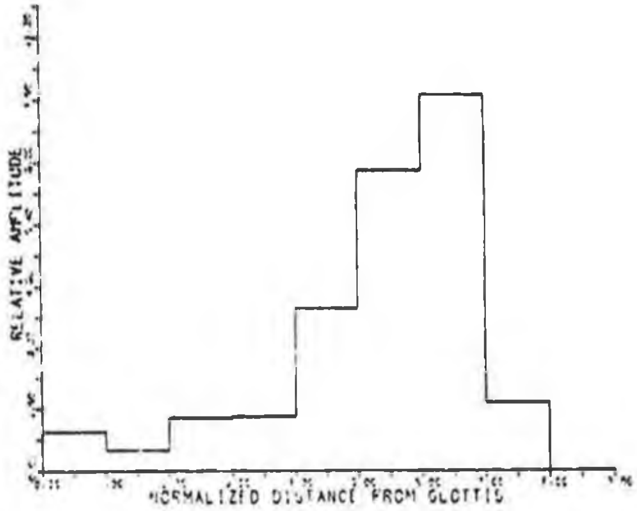
(b) First order Preemphasis method

Fig 5.21 Area Functions, Formants and Bandwidths for vowel /er/



	1	2	3	4	
F	616	1088	2223	3206	Hz
B	42	312	196	79	Hz

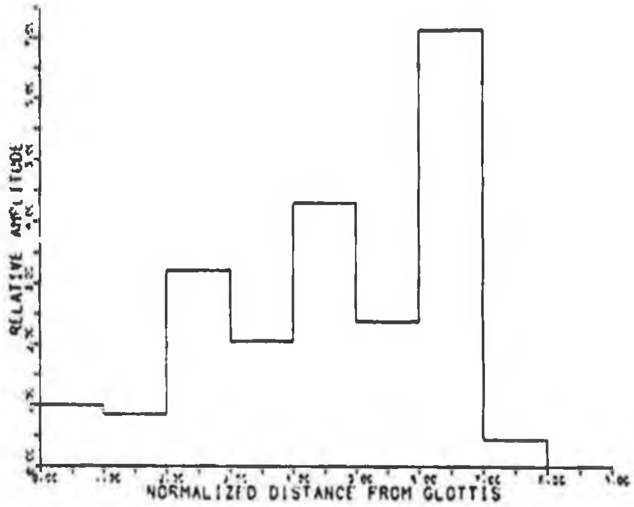
(a) CGI method



	1	2	3	4	
F	604	1106	2195	3195	Hz
B	105	778	344	83	Hz

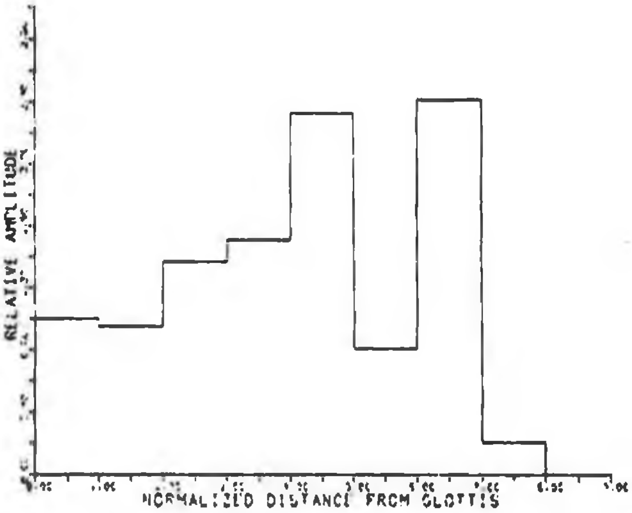
(b) First order Preemphasis method

Fig 5.22 Area Functions, Formants and Bandwidths for vowel /a/



	1	2	3	4	
F	341	1216	2014	2781	Hz
B	35	134	270	109	Hz

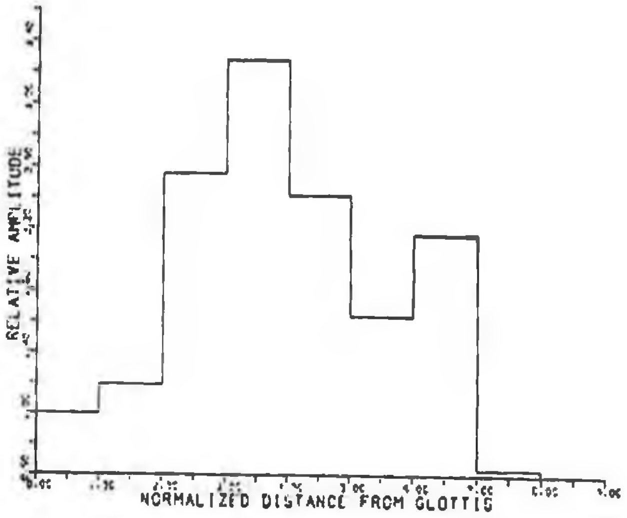
(a) CGI method



	1	2	3	4	
F	321	1269	1902	3109	Hz
B	189	429	436	520	Hz

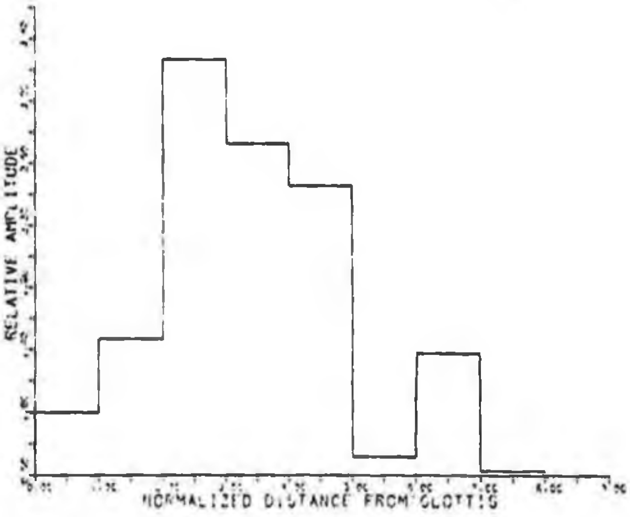
(b) First order Preemphasis method

Fig 5.23 Area Functions, Formants and Bandwidths for vowel /u/



	1	2	3	4	
F	414	1607	2192	3381	Hz
B	81	185	283	296	Hz

(a) CGI method



	1	2	3	4	
F	362	1724	2265	3146	Hz
B	119	334	527	303	Hz

(b) First order Preemphasis method

Fig 5.24 Area Functions, Formants and Bandwidths for vowel /ae/

5.5.3 Explanation of Results

To understand the results, it is necessary to consider the analysis under two separate headings i.e. inherent properties of the LPC analysis, and the corresponding effect of source tract interaction.

5.5.3.1 Autocorrelation vs. Covariance Methods

For comparable frame lengths, of the order of two to three pitch periods, both the covariance and autocorrelation method yield similar results. In general long windows for the autocorrelation method provide poor time resolution, with variation in formants smeared or averaged out. Shorter windows have bad frequency resolution, and are not recommended. For shorter frame lengths, it is acknowledged that the covariance method is the most accurate, although instability problems may arise.

5.5.3.2 Source-Tract Interaction

The perceptual significance of source-tract interaction due to the supraglottal pressure, as discussed in Section 2.3.1, is the subject of much discussion. Its effects on asynchronous and pitch synchronous analysis are quite pronounced, with formant shifts and significant formant damping, which in turn affect the glottal waveform extracted. It is generally agreed that the main effect of source tract interaction is a widening of bandwidths, particularly of the first two formants. This is apparent from examining the spectra obtained from the two methods being compared.

For the above reasons, CGI analysis is preferred. However it is claimed by Holmes [39] that even for this method, source tract interaction cannot be discounted completely, and base line drift, for example, can result in significant formant and bandwidth errors. This would explain the need for the interactive vocal cord model described in Section 2.3.1. According to Anath *et al.* [40], however, it can be discounted except in cases of vowels with a very low first formant. This is attributed to [41] the fact that the assumption of plane wave propogation breaks down at frequencies below about 300Hz, and non-negligible interaction takes place. This is borne out by the glottal waveform for the vowel /i/, shown in Fig 5.25 which contains remains of formants in some cycles. However, the CGI waveform will still be more accurate than the preemphasis method. Due to this interaction, the detection of the CGI region is more difficult for vowels with low first formant. This is shown in Fig 5.26, which is the NMSE waveform obtained for the vowel /u/. Here, the CGI could not be obtained easily from manual inspection. However, the method for extracting the CGI proposed here resulted in the ripple free waveform of 5.14b, because its general location was predefined in the algorithm.

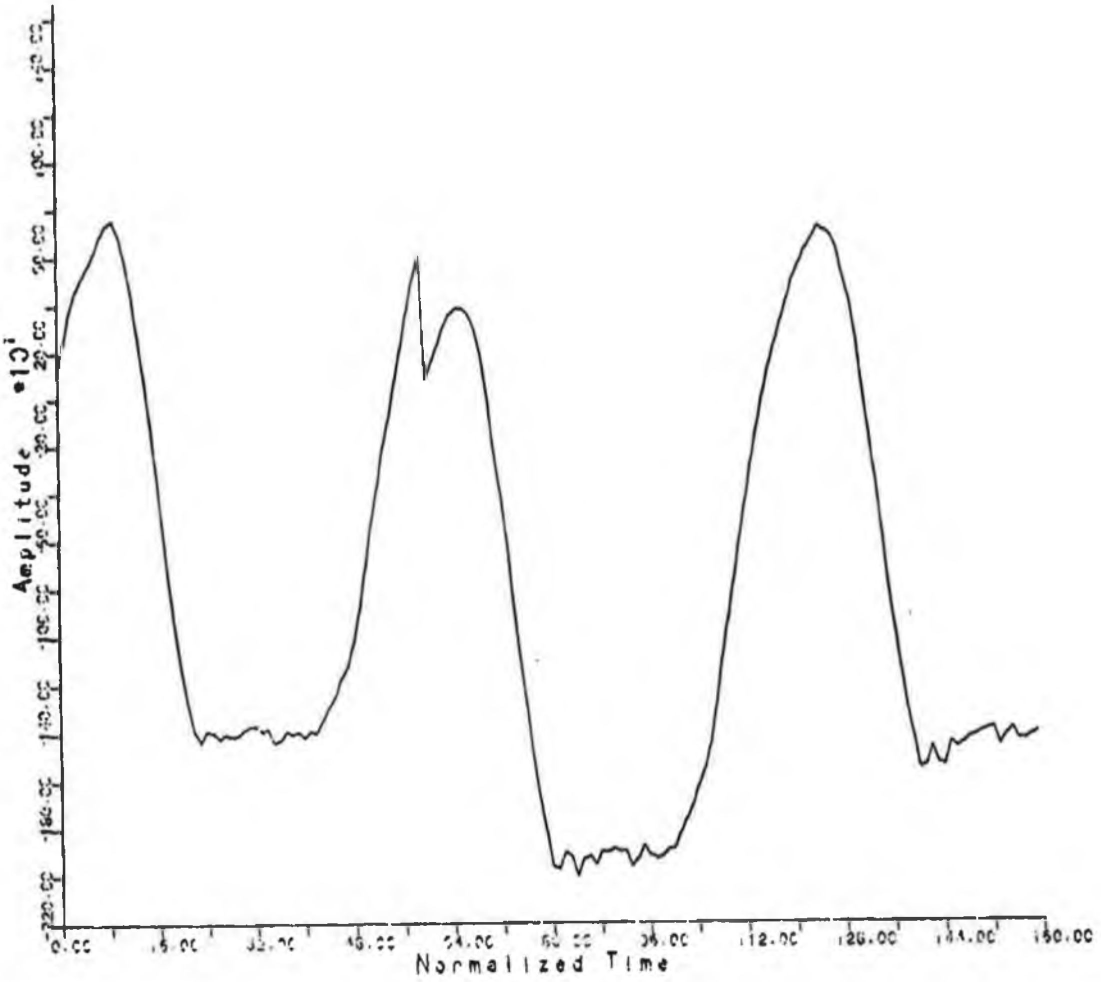


Fig 5.25 Glottal Waveform (CGI analysis) for the vowel /i/

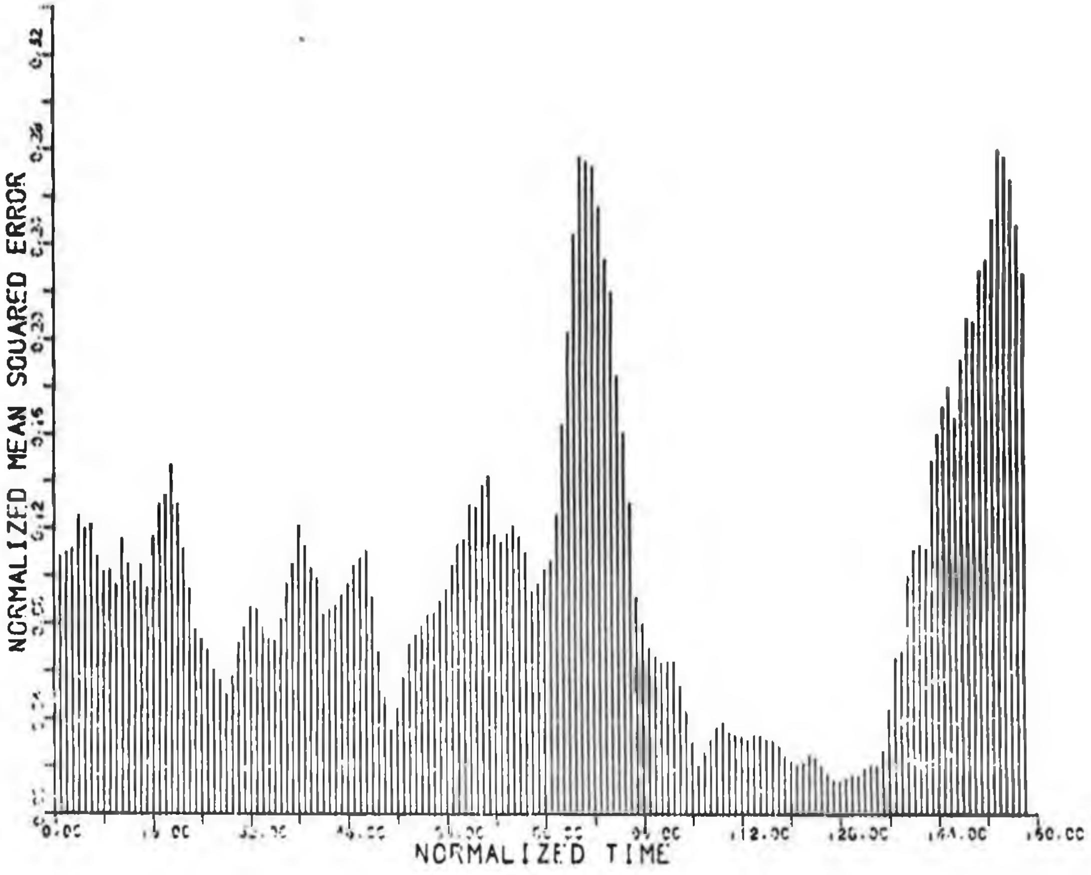


Fig 5.26 Normalized Mean Squared Error for the vowel /u/

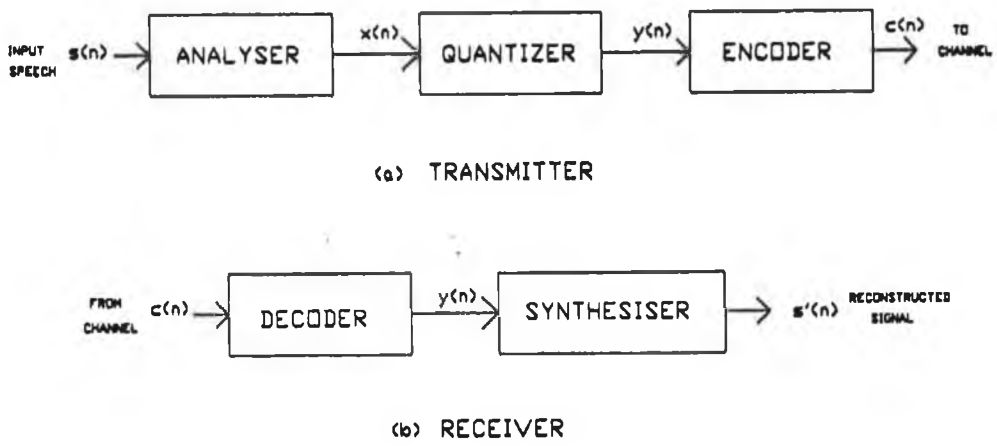
CHAPTER 6 ARTICULATORY SPEECH CODING

6.1 Introduction

Methods for using the closed glottal interval analysis described in the previous chapter, in conjunction with the ASY synthesiser, to develop an articulatory coding system are discussed. This includes a general discussion of speech coding, in particular articulatory coding, and a comparison of quantization methods, including an analysis of suitable distortion measures. A method for generating an articulatory codebook using existing techniques is presented, along with a procedure for extending it to a linked codebook with the acoustic domain. The limitations of the method are then discussed, and a new proposal for generating an optimum articulatory codebook is investigated. Finally, the design of a glottal codebook is discussed.

6.2 General Speech Coding System

A typical speech coding system is shown in Fig 6.1. The input speech, s(n), is analysed, and a set of parameters, x(n), are extracted.



(a) TRANSMITTER

(b) RECEIVER

Fig 6.1 Speech Coding System

These continuous amplitude signals are then quantized to y(n) and encoded into transmission parameters c(n) before being sent over a communications channel. At the receiver, assuming a noise free channel, the signal, c(n), is decoded and the speech is reconstructed from the resulting parameters using a speech synthesiser.

6.3 Quantization

Quantization is the process whereby continuous amplitude signals are converted to discrete amplitude signals, i.e. from above

$$y = Q(x) \tag{6.1}$$

where Q is the quantization transformation. There are a certain number of allowable levels, dependent on the bit allocation for each parameter, or set of parameters. There are two main types of quantization:

(i) Scalar: In this case each parameter from a set is quantized independently.

(ii) Vector: Here, each set of parameters, known as a vector, is quantized as a block, and is represented by a single symbol. This can result in great reductions in bit rates, and is the type to be considered here.

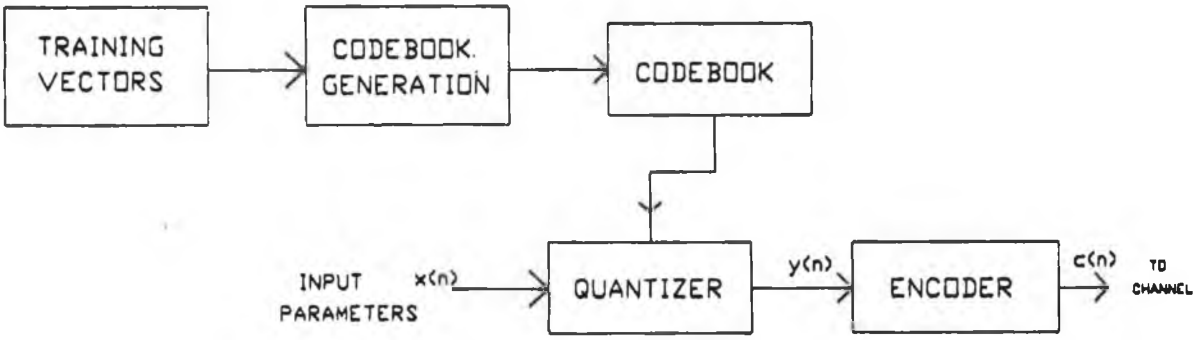


Fig 6.2 Vector Quantization

6.3.1 Vector Quantization

The application of Vector Quantization (VQ) to speech coding was first investigated by Gray [42]. The usual process of VQ in speech coding is shown in Fig 6.2. There are two main steps. First a group, or codebook, of representative vectors is generated from a large set of training vectors. This codebook should be the best possible representation of the entire space of vectors, and should be designed to minimize the overall quantization distortion. It is generated by partitioning the vector space into

$$L = 2^B \qquad (6.2)$$

partitions, where B is the number of bits available to represent each vector. Each partition is known as a cell, i.e. the partition,

$$P = \{ C_i \ ; \quad 1 \leq i \leq L \} \qquad (6.3)$$

defines L regions (clusters), each represented at its centre by its centroid (template). Thus each vector of the training set is allocated to a particular cluster, which is chosen so as to minimize the overall quantization error between the training data and templates. Many iterative clustering algorithms are available [43,44].

Once the codebook of templates has been generated, each input vector is quantized by searching the codebook to find its closest match, according to a suitable distortion measure.

The main advantage of VQ is that once a suitable vector (of arbitrary length) is chosen from the codebook, a symbol to represent this vector is transmitted from the encoder, rather than the vector itself. Thus a significant saving in bit rates is achieved. The vector is then reconstructed from the symbol at the receiver by the decoder. Using lower bit rates carries the penalty of lower fidelity. So distortion minimization is very important.

VQ is especially useful when the vector parameters have statistical interdependence. It has been shown [45] that, in these cases particularly, it is far more economical than scalar quantization.

6.4 Distortion Measures

Establishing a suitable distortion measure is of major importance in coding LPC parameters, as it is used in both the codebook generation stage, and in the quantization of the speech to be transmitted.

Distortion measures used in coding have the following properties:

(i) It must be easy to compute

(ii) It must be easily analysed

(iii) It should be subjectively relevant i.e. differences in distortion values should indicate similar variations in speech quality.

Three most common categories of distance measures will be defined here, to be enlarged on in Sections 6.4.1 - 6.4.3. In all cases, the vector dimension is denoted as M, corresponding to the order of the prediction filter.

(i) The most mathematically obvious, and also the most common measure is the mean squared error. This is defined as

$$d(x,y) = \frac{1}{M} (x - y)^T (x - y) \tag{6.6}$$

$$= \frac{1}{M} \sum_{i=1}^{M} (x_i - y_i)^2 \tag{6.7}$$

It can be applied to many coefficient transformations as discussed below.

(ii) A weighted mean squared error distortion measure is sometimes used, in order to emphasise certain parameters which are more relevant.

This is generally defined as

$$d(x,y) = (x - y)^T W (x - y) \tag{6.8}$$

where W is a constant weight matrix.

(iii) A third type of measure is a form of (ii) where the weighting matrix is variable, dependent on the input vector, x. In this category is a well known LPC distortion measure, named after its developers, Itakura and Saito [48].

6.4.1 Distortion Measures based on the Mean Squared Error

The distortion measures considered here are based on the predictor coefficients, and corresponding transformations.

(i) The simplest LPC distortion measure is the straight forward difference of predictor coefficients, $\{a\}$. Thus, if $\{\tilde{a}\}$ is an approximation to $\{a\}$, the distortion measure is defined as:

$$d(a,\tilde{a}) = \frac{1}{M} \sum_{i=1}^{M} (a_i - \tilde{a}_i)^2 \tag{6.9}$$

(ii) Problems with instability may arise when quantizing the predictor coefficients. Interpolation between two vectors of stable coefficients may result in unstable filters. Also, less than perfect accuracy of transmission can also lead to instability. For this reason, the PARCOR coefficients, $\{k\}$ are preferred. Since, when stable, they are bounded by unity, it is easy to detect instability, and interpolation between two sets of PARCOR coefficients is guaranteed to result in a stable filter.

For values of $\{k\}$ approaching unity, the poles approach the unit circle, and small changes in $\{k\}$ can result in large changes in the spectrum. Also, while all

PARCOR coefficients are bounded by unity, there is a non-uniform distribition of coefficients over this interval, with the distributions of all except the first two coefficients concentrated around zero (the first two are close to unity). Thus uniform quantization is both wasteful and illadvised.

For this reason, PARCOR coefficients are usually transformed into another set of coefficients that exhibit lower spectral sensitivity. A particular transformation, and one which is often used, is that to the log area ratios, (LAR), which have the property that small changes in the LAR are approximately proportional to corresponding changes in the log spectrum of H(z). These are defined as follows:

$$G_i = 0.5 * \log \left[\frac{1 + k_i}{1 - k_i} \right] \qquad 1 \leqq i \leqq M \qquad (6.10)$$

Thus these parameters are suitable for a uniform quantization by the mean squared error distortion measure.

(iii) Another coefficient transformation used in LPC is the transformation to the corresponding cepstrum coefficients. These are spectral parameters, defined as

$$c_n = \frac{1}{2\Pi} \int \log \left| S(\omega) \right| e^{jn\omega} \delta\omega \qquad (6.11)$$

where

$$S(\omega) = H(z) \Big|_{z = e^{j\omega}} \qquad (6.12)$$

It can be shown [46] that the appropriate LPC transformation, which obtains the cepstrum coefficients of the LPC derived spectrum envelope from the predictor coefficients is

$$c_m = - a_m - \sum_{n=1}^{m-1} (m/n)\, c_n\, a_{m-n} \qquad 1 \leqq i \leqq M \qquad (6.13)$$

It has been noted by Shirai [47] that the lower order cepstrum coefficients show the global spectral shape. For this reason, they can be omitted from the distortion measure to emphasise the matching of the pole structure. Thus a modified distortion measure for the cepstrum coefficients is

$$d(x,y) = \frac{1}{M} \sum_{i=n}^{M} (x_i - y_i)^2 \qquad n > 3 \qquad (6.14)$$

6.4.2 Distortion Measures based on the Weighted Mean Squared Error

An example in this category is a weighted measure of formant and bandwidths differences. They are first normalized with respect to average formant values, and extra weighting is put on matching the first three formants in particular. Another example, using articulatory parameters will be discussed in Section 6.6.3

6.4.3 Itakura - Saito Distortion Measure

Since the Itakura-Saito distortion measure, which is based on the vector position in parameter space, was first postulated [48], it has been used extensively in vector quantization of speech. From Fig 6.1, it can be seen that there are two sources of error introduced in a speech coding system, that introduced during LPC analysis, and the error due to quantization. LPC analysis is designed to minimise the residual (error) energy. Thus ideally the quantization step should also minimize this error. Using statistical principles, Itakura showed that the log likelihood ratio can be expressed as the log of the ratio of prediction residuals.

Given a segment of speech, X, with estimated predictor coefficients, {a}, a distortion measure between X and a template $\{\tilde{a}\}$ which is a centroid from the codebook, is sought. The log of the conditional joint probability density, known as the log likelihood ratio, is denoted as

$$\log [\ p(X,\tilde{a})\ ] = L(X,\tilde{a}) = L(a,\tilde{a}) \qquad (6.15)$$

It can be shown [48] that this ratio may be reduced to a powerful distortion measure, i.e.

$$d(a,\tilde{a}) = \log \left| \frac{\tilde{a}\ V\ \tilde{a}^{T}}{a\ V\ a^{T}} \right| \qquad (6.16)$$

V is the correlation matrix obtained during LPC minimization. Usually the distortion measure is defined for the autocorrelation method of linear prediction, so that

$$v(i) = \frac{1}{N} \sum_{n=1}^{N-i} x(n)\ x(n+i) \qquad 1 \leq i \leq M \qquad (6.17)$$

Numerical methods are available for simplifying this distortion measure, in order to save on matrix multiplication. It is noted that the correlation matrix is a by-product of LPC, and does not have to be recomputed.

The corresponding matrix for the covariance method is the covariance matrix, as already discussed in section 4.3.3. The Itakura-Saito distortion measure is not symmetric, since for any two vectors, u and v, $V_u \neq V_v$. Because of this an asymmetrical distortion measure is proposed, such that

$$d(X,\tilde{a}) = 0.5 * (\ d(a,\tilde{a}) + d(\tilde{a},a)\ ) \qquad (6.18)$$

i.e.

$$d(X,\tilde{a}) = 0.5 * (\log \left| \frac{a\ V'\ a^{T}}{\tilde{a}\ V'\tilde{a}^{T}} \right| + \log \left| \frac{\tilde{a}\ V\ \tilde{a}^{T}}{a\ V\ a^{T}} \right|) \qquad (6.19)$$

where V' is the corresponding matrix obtained from $\{\tilde{a}\}$. This matrix must be stored for each codeword.

6.5 Articulatory Speech Coding System

In Fig 6.1, the type of synthesiser used at the receiver determines the type of parameters used for coding. In this research, an articulatory synthesiser is used, hence the articulatory parameters must be obtained from the speech signal, both for on-line coding and codebook generation. This will be discussed further in Chapter 7, suffice to say here that it is a non-trivial problem, which has no simple solution. It is certainly impossible to do on-line.

To overcome this problem, the idea of a linked codebook i.e. a look-up table of acoustic parameters matched to corresponding articulatory parameters is proposed. The procedure for generating such a codebook is shown in Fig. 6.3.

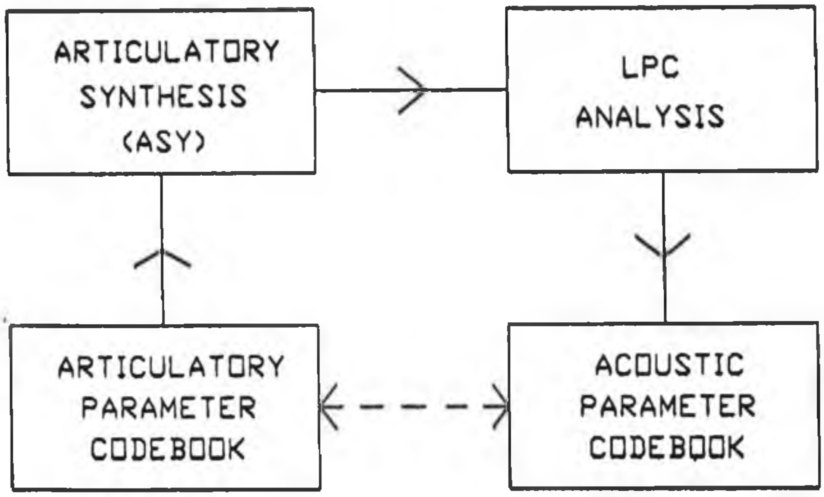

ARTICULATORY SYNTHESIS (ASY)
LPC ANALYSIS
ARTICULATORY PARAMETER CODEBOOK
ACOUSTIC PARAMETER CODEBOOK

Fig 6.3 Construction of Linked Codebook

First, the articulatory space is sampled in a representative manner to generate an articulatory codebook. Thus centroids are obtained in the articulatory domain. Once the articulatory codebook is generated, speech is synthesised from each centroid, and the corresponding acoustic parameters extracted. This is the basis of the linked codebook, or look-up table. Thus once this linked codebook is created, speech coding is carried out, as shown in Fig 6.4. Acoustic parameters are extracted from the incoming speech, and the closest match in the acoustic part of the codebook is found using a suitable distortion measure. The corresponding articulatory parameters are found in the look-up table, and these are encoded for transmission.

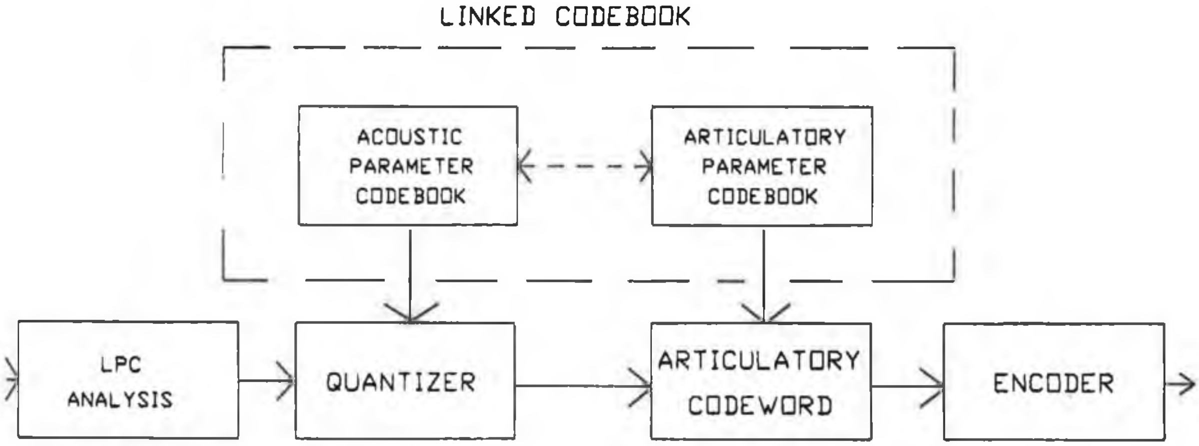


Fig 6.4 Articulatory Speech Coding System

6.6 Generation of the Articulatory Codebook

The procedure for sampling the articulatory space is more difficult than for usual codebooks, particularly as centroids obtained in the acoustic domain do not, in general, coincide with centroids on the articulatory domain. Two methods are proposed here, the first of which is used for evaluating distance measures.

6.6.1 Sensitivity analysis method

In this method, a form of which has been used by Schroeter *et al.* [49] for articulatory coding, a training sequence is not used. Instead the positions of certain key features (in this case vowels) are obtained in the articulatory domain, and interpolation carried out between these positions to generate a codebook of shapes. The procedure carried out here is based on a sensitivity analysis of the articulatory parameters of ASY, carried out by Kuc *et al.* [50] for vowel recognition applications. It was observed from analysis that the order of sensitivity of the articulatory parameters, in order of greatest to least sensitivity was as follows: jaw angle, tongue body coordinates, lip coordinates, tongue tip coordinates and hyoid, all as defined previously in Section 2.4.1. For quantization

four extreme vocal tract shapes in the articulatory space were identified by the vowels /a/, /i/, /u/ and /ae/. The range of each parameter between these extreme shapes was established, and divided into equal increments, the number of increments depending on the sensitivity. The number of increments were as follows: jaw angle(10), tongue body, C(length = 8,angle = 8), lips, L(height = 4, protusion = 2), tongue tip, T(length = 0, angle = 3), hyoid, H(0).
Those parameters which were not quantized were set at their mean values obtained from the four extreme positions. This quantization produced 15,360 discrete vocal tract shapes.

6.6.2 Limitations of Sensitivity Analysis method

While the sensitivity analysis method of generating the articulatory codebook should sample the articulatory space quite representatively, there is no guarantee that this codebook is the optimum one. No clustering is done as such, because there is no training data used, so no distortion is measured. For vector quantization the number of bits used to describe a vector is usually about B = 10. So the average codebook size is

$$L = 2^{10} = 1024 \qquad (6.20)$$

Codebook sizes greater than this are usually too large to handle, in terms of both storage costs and particularly computational considerations e.g. codebook searches. Attempts to reduce the number of shapes have been tried by proportionally reducing the number of increments used. This only reduces fidelity even more.

The basic problem is that the codebook is generated purely from synthetic shapes. For a codebook of size L, generated by clustering, the number of training data vectors is recommended to be $\geq$ 50L, which for this case would be the order of 50,000 vectors. The ideal situation would be to use real speech to generate the codebook, which returns the problem to that of estimating the articulatory parameters from the speech wave.

6.6.3 Training set method

A method has been proposed by Shirai et al [47] for estimating the articulatory parameters from the speech wave, using a non-linear iterative procedure. It has been used successfully for Japanese vowel recognition. This procedure will be described in Chapter 7.

Using this method, applied to the ASY synthesiser, a large training set of articulatory parameters could be obtained directly from the speech wave. These articulatory parameters would then be clustered in the articulatory domain, using a suitable distortion measure. The distortion measure proposed here would be a weighted mean squared error of articulatory parameters, with the weights determined from the relative sensitivity of each parameter, as outlined previously. So centroids are obtained in the articulatory domain, speech is synthesised from these, and the corresponding acoustic parameters are obtained. These parameters are then used to construct a linked codebook in the same manner as the sensitivity analysis method.

6.7 Linked Codebook Generation

The generation of the linked codebook involved synthesising speech from the 15,360 shapes obtained from quantization of the articulatory space, as discussed in Section 6.6.1. For this, ASY, which is essentially an interactive synthesiser, was converted for use as a subroutine. ASY was written in Fortran, so this involved interfacing C and Fortran subroutines. For each articulatory shape, a speech segment of approximately 20ms long was generated, using default source parameters, i.e. open quotient of 0.5, speed qoutient of 3.0, and pitch of 100Hz. ASY generates speech at 20Khz, so this speech had to be down-sampled to 7.5Khz (the sampling rate of the incoming speech), and then analysed using the closed glottal interval analysis of Chapter 5.

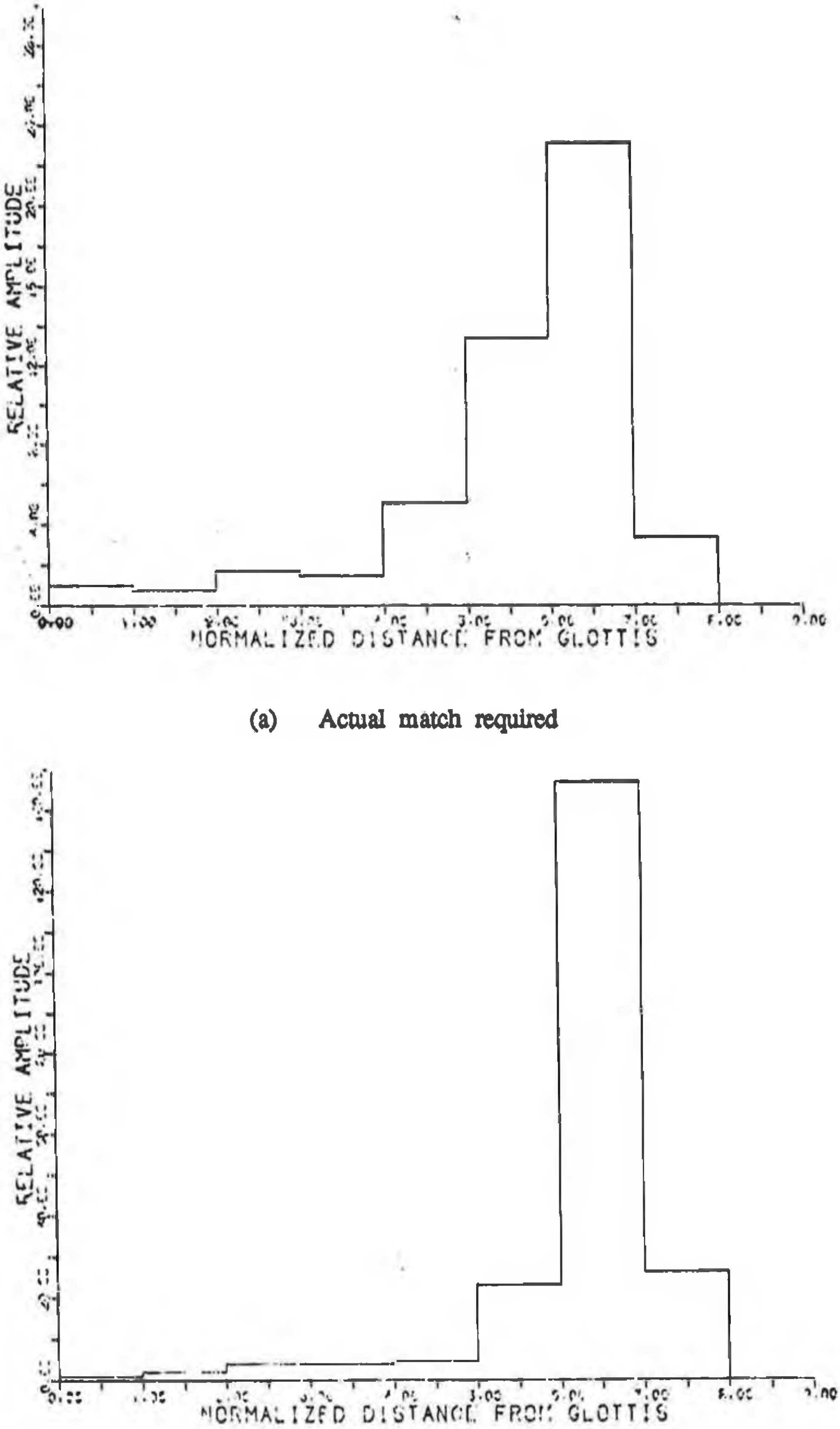
Initially, it was proposed to compute the transfer functions from for the look-up table directly from the cross-sectional areas, as described in Section 3.3. However it was felt that the acoustic parameters of the model and of the real speech should be extracted under identical conditions, otherwise the results would be inconsistent. Only the first four formant frequencies could have been compared directly, as the LPC transfer function does not correspond to the transfer function of ASY, which as well as incorporating losses, actually extracts a much larger number of formants, due to the number of cross–sectional areas used (greater than twenty). By using the same method for both, limitations of the LPC analysis are inherent in both sets of parameters, and are effectively cancelled out.

The linked codebook generated from an articulatory codebook generated from using a training set of real speech data would be generated in a similar manner, with speech being synthesised from the centroids obtained from articulatory clustering.

6.8 Evaluation of Distortion Measures

A study of the discussed distortion measures was undertaken for various vowels. The closest match, according to the minimum distance for each type of measure, was found from the acoustic part of the codebook described above.

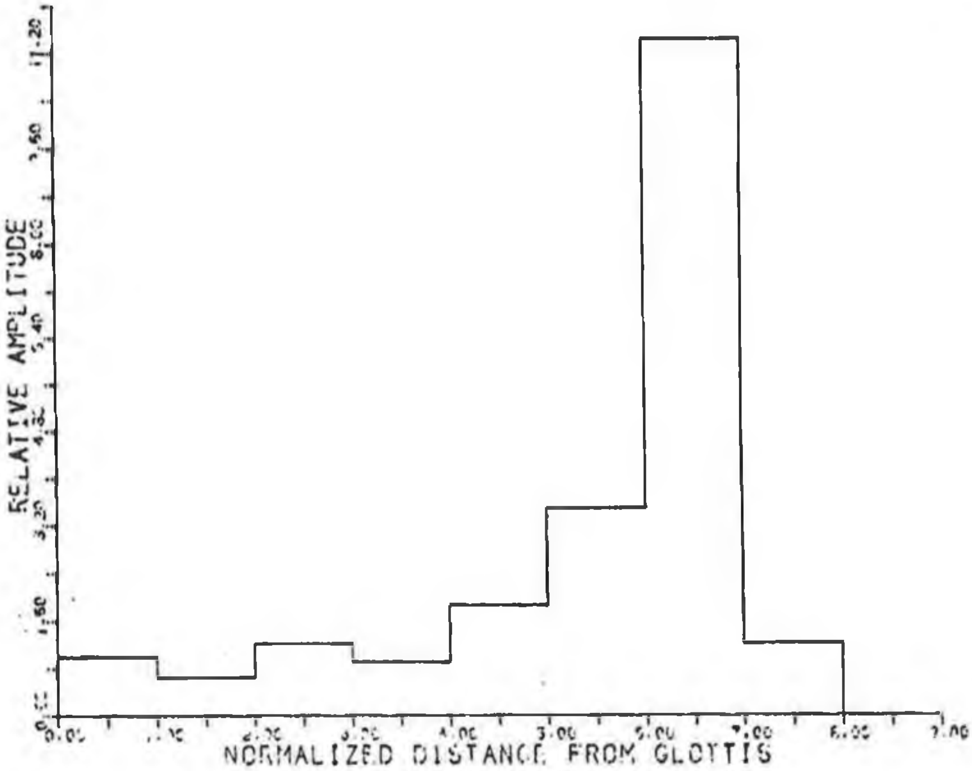
An example of the chosen vectors from the codebook, and their corresponding area functions are shown in Fig 6.5, for the vowel /a/. In general, all the distortion measures yielded similar results. The closest matches obtained were from the log area ratio and covariance measures, whereas those obtained from the predictor and cepstrum coefficients were not as accurate. The high order cepstrum coefficients produced the same results as the ordinary mean squared error cepstrum measure. The Itakura-Saito autocorrelation measure yielded the worst results, as would be expected, since the LPC autocorrelation method was not used. The formant and bandwidth measures were not very consistent either. The difficulty with this method is choosing the right weights, and in general methods which essentially use normalized parameters, such as the predictor coefficients, are preferred.



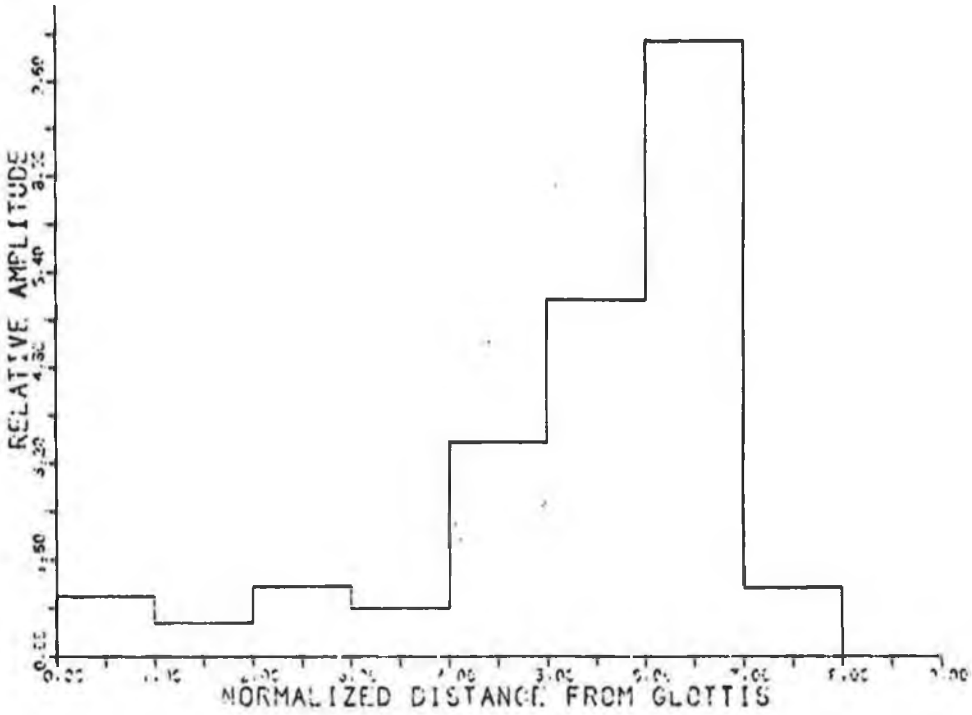
(a) Actual match required

(b) Itakura-Saito Method

Fig 6.5 Area Functions obtained from various distance measures

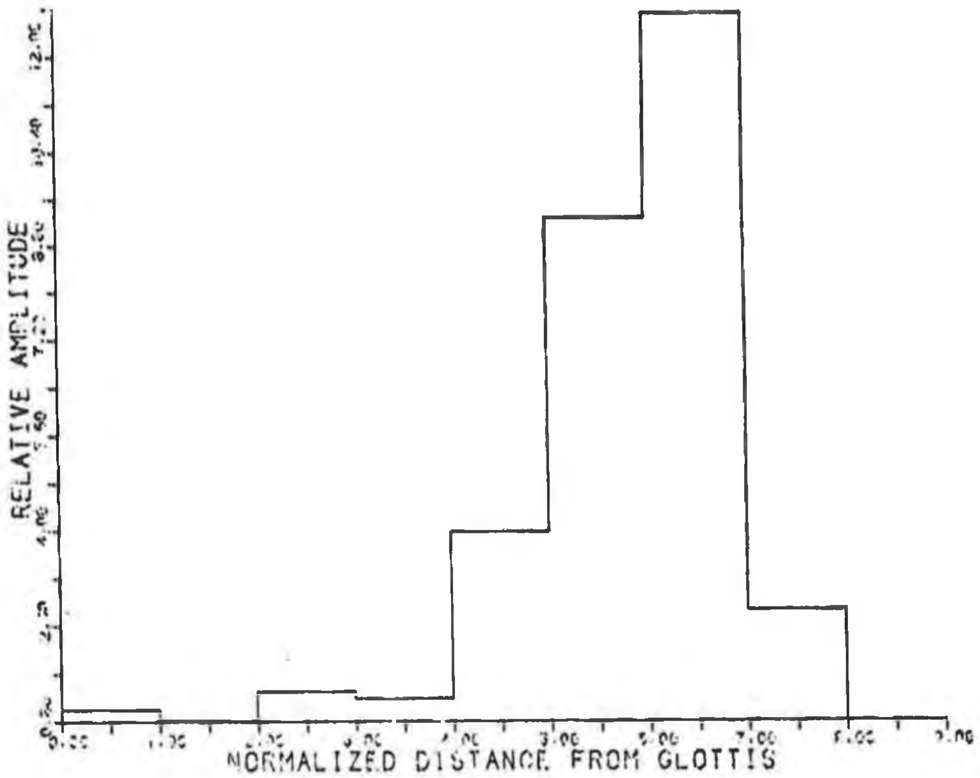


(c) Covariance Matrix Method

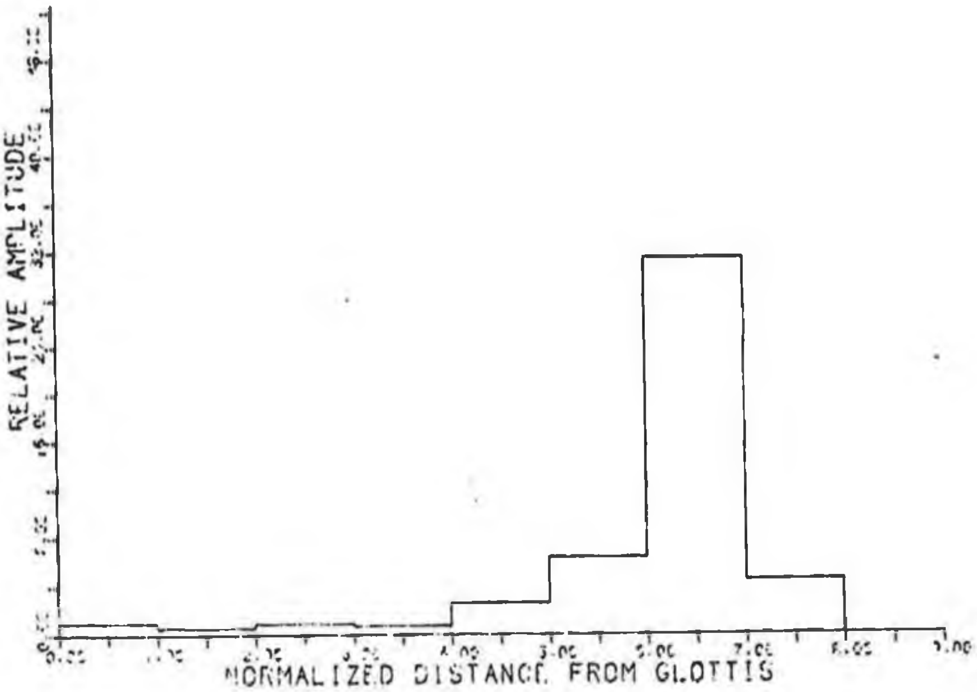


(d) Log Area Ratio Measure

Fig 6.5 Area Functions obtained from various distance measures

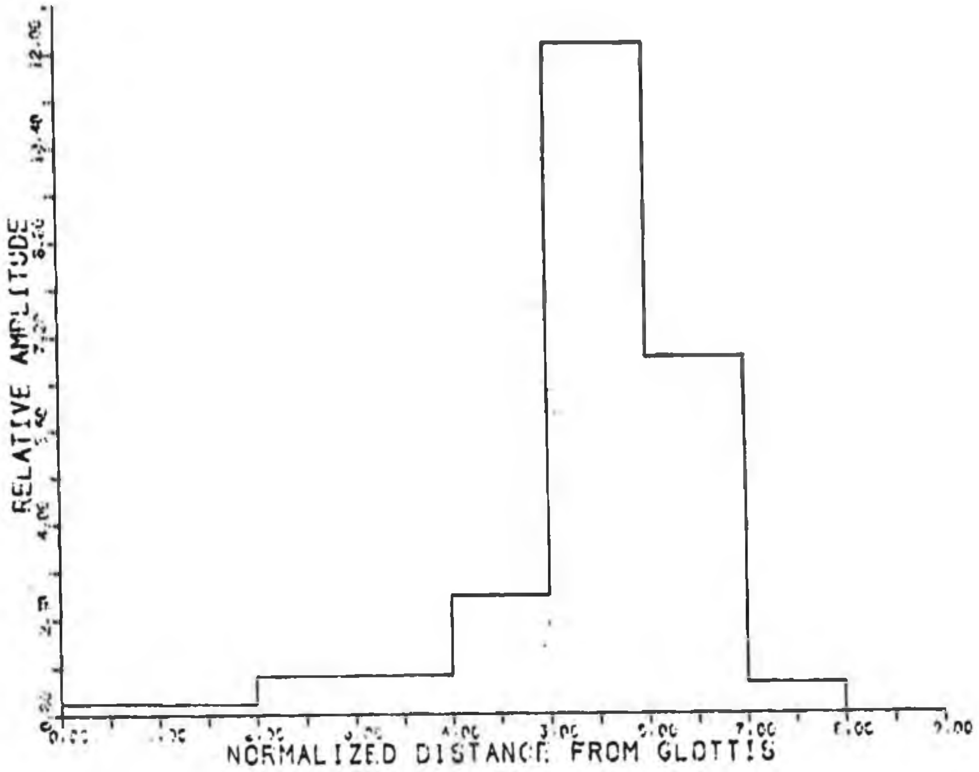


(e) MSE of Cepstrum Coefficients



(f) MSE of predictor coefficients

Fig 6.5 Area Functions obtained from various distance measures



(g) Weighted MSE of formants and bandwidths

Fig 6.5 Area Functions obtained from various distance measures

It must be said, however, that a true evaluation could only be done in a full speech coding system, by comparing the results for large amounts of parameters, and by listening to the transmitted speech. However, for the reasons discussed in Section 6.4.3, it is likely that the covariance measure, developed along the same lines as the Itakura-Saito distortion measure, should yield the best results. The log area ratios would also be very useful, particularly for articulatory applications, as it is concerned with minimizing the error in vocal tract shape.

Another problem with the analysis is that as ASY generates speech at a 20Khz sampling accuracy, down-sampling this will obviously have a detrimental effect. ASY may be converted easily enough to output speech at 10Khz, and sampling rates below this are not recommended for articulatory synthesis, as its advantages over LPC synthesis would no longer be apparent. So, it is suggested, for future work, that the input speech should also be sampled at 10Khz, and the filter order for LPC analysis increased to 10. Because of the relatively low sampling rate, higher formants (above 3500Hz) will not be detected, and sometimes only three formants will be extracted. This is another reason why direct comparison of formants and bandwidths was not very successsful in this analysis.

6.9 Glottal Codebook Design

The design of a glottal codebook to best represent the four source parameters, i.e. pitch, amplitude of glottal pulse, open quotient and speed quotient, is straightforward. The parameters are extracted from the glottal waveform obtained from the algorithm for CGI analysis (Fig. 5.10), using the algorithm described in Section 5.4 (Fig. 5.11). A fairly crude quantization should suffice, e.g. 3-4 bits per parameter, if scalar quantization is used. If vector quantization is used, lower bit rates should be possible, although the fact that the vector parameters are essentially statistically independent of each other may mean that the extra computation and resources required for codebook generation is not worthwhile. If vector quantization is chosen, an example of an appropriate clustering algorithm would be the modified K-means algorithm [42].

CHAPTER 7 ESTIMATION OF ARTICULATORY PARAMETERS FROM THE SPEECH WAVE

7.1 Introduction

A general discussion of the inverse problem of the vocal tract is presented here, followed by a particular method (Shirai's [47]), for which an algorithm is derived. Analysis conditions are discussed at length, and possible reasons for the disappointing results are presented. Ideas for improvement are then proposed, including the need to try a wide range of methods.

7.2 Inverse Problem of the Vocal Tract

Let $\{y\}$ be an M - dimensional vector which represents the acoustic parameters of a speech wave, and $\{x\}$ an N - dimensional vector to represent its corresponding articulatory parameters. The acoustic parameters may be expressed as a function of the articulatory parameters

$$y = h(x) \tag{7.1}$$

where h(x) is the vocal tract function. The inverse problem

$$x = h^{-1}(y) \tag{7.2}$$

of the vocal tract is thus defined as the problem of estimating the articulatory parameters from the acoustic parameters, or from the speech wave.

Direct methods for determining the vocal tract shape from the speech wave are available, e.g. Wakita's method [20], discussed in previous chapters. There are inherent problems with these methods. As discussed in Section 3.2, a lossless tube model of the vocal tract is assumed, with ideal boundary conditions for the glottis and lips. This approach leads to ambiguity in that two different area functions can represent the same vocal tract transfer function, depending on the imposed boundary conditions. In addition, no analytical solution exists for the lossy case.

In reality, h(x) is a non-linear function of {x}. There are two main sources of this non-linearity. Firstly, the fundamental ambiguity, known as the 'ventriloquist effect' is apparent, where different vocal tract shapes can produce an identical transfer function. Secondly, the articulators themselves impose natural constraints on the vocal tract shape.

Because of the absence of analytical solutions for the lossy case, two alternatives, based on numerical methods, are usually investigated, i.e. regression analysis and constrained optimization.

7.2.1 Regression Analysis

The first is a direct approximation approach, i.e. representing $h^{-1}(y)$ as a combination of simple functions e.g. piecewise linear or polynomial. These regression techniques have been shown by Atal [51] to give good results, provided that enough non-linear terms are contained in the approximating function. A training set of (x,y) data is required for this method, which is obtainable from the model itself.

7.2.2 Constrained Optimization

The second approach is that of an non-linear optimization of parameters, based on the minimization of the error between the model output and the measured data. This approach is usually preferred, as it should yield more accurate results, and is more subjectively meaningful in relation to the non-linear estimation problem. Also it is based on real speech, rather than synthetic, as in Section 7.2.1.

The inverse problem, as discussed in this research, is therefore a non–linear optimization of parameters under a certain criterion, and must be solved iteratively. Unfortunately, this transformation is ill-posed i.e. known problems are uniqueness of solution and stability of the convergence. To convert it to a well-posed problem, constraints must be imposed on the range of the articulatory parameters and an appropriate initial estimate should be obtained. Many optimization algorithms have been proposed [52-55], basically differing in the type of constraints imposed and choice of initial estimate. The method chosen here was that of Shirai et. al [47], because, as well as imposing comprehensive constraints on the range of the articulatory parameters, it has claimed to yield excellent results for Japanese vowel recognition.

7.3 Shirai's Method

This method is essentially a modified version of the Newton-Raphson formula

$$x^{i+1} = x^{i} + \frac{f(x)}{f'(x)} \qquad (7.3a)$$

which may also be written as

$$x^{i+1} = x^{i} + \lambda\, f(x) \qquad (7.3b)$$

where λ is a convergence parameter, which controls the speed of convergence. Constraints on the direction of convergence are added to this basic formula.

Let $\{y\}$ be the acoustic parameters measured accurately from the speech wave. These parameters may be spectral parameters such as cepstrum coefficients or LPC parameters. For each frame, the best estimate $\{\tilde{x}\}$ of the articulatory parameters is obtained so as to minimise the cost function

$$J(x) = |y - h(\tilde{x})|_R^2 + |\tilde{x}|_Q^2 + |\tilde{x} - l|_\Gamma^2 \qquad (7.4)$$

where R, Q and Γ are weighting matrices and l is the articulatory estimate of the previous frame. R is an M x M matrix, Q is an N x N matrix , and Γ is an N x N matrix. The notation above results in a scalar distance measure for each group of vectors.

The first term is the weighted square error between the measured acoustic parameters and those of the model. The second term restricts the deviation from the neutral position, while the third term restricts the deviation from the estimate of the previous frame.

It can be shown [47] that the solution minimising the function J is obtained by the following iterative form:

$$\tilde{x}^{i+1} = \tilde{x}^{i} + \lambda_i \, \delta\tilde{x}^{i} \qquad (7.5)$$

where

$$\delta\tilde{x}^{i} = \left| \left[\frac{\delta h(\tilde{x}_k^{i})}{\delta x} \right]^T R \left[\frac{\delta h(\tilde{x}_k^{i})}{\delta x} \right] + Q + \Gamma \right|^{-1}$$

$$* \left| \left[\frac{\delta h(\tilde{x}_k^{i})}{\delta x} \right]^T R \, (y_k - h(\tilde{x}_k^{i})) - Q \, \tilde{x}_k + \Gamma(1 - \tilde{x}_k^{i}) \right| \qquad (7.6)$$

where *i* is the iteration number, and *k* the frame number. λ_i, the parameter which is used to monitor the speed of convergence, can be changed as the iteration proceeds. It is often called the stepsize parameter or weighting constant.

Eqn (7.5) and (7.6) together are of the form

$$\tilde{x}^{i+1} = \tilde{x}^{i} + \lambda_i \{ B^{-1} A \} \qquad (7.7a)$$

where A and B are matrices. In terms of scalar parameters, this can be written in the form

$$\tilde{x}^{i+1} = \tilde{x}^{i} + \frac{A}{B} \qquad (7.7b)$$

As A contains the term (y - h($\tilde{x}$)) and B contains the derivative of h($\tilde{x}$), this is in the same form as eqn. (7.3a).

The term $\{\delta h(\tilde{x}_j) \,/\, \delta x_j\}$ is a partial derivative with respect to each articulatory parameter $\tilde{x}_j$ in $\{\tilde{x}\}$. Thus since h($\tilde{x}$) is an Mx1 matrix, its derivative is an MxN i.e.

$$\left[\frac{\delta h}{\delta x}\right] = \begin{bmatrix} \frac{\delta h_1}{\delta x_1} & \cdots & \frac{\delta h_1}{\delta x_N} \\ \vdots & & \vdots \\ \frac{\delta h_M}{\delta x_1} & \cdots & \frac{\delta h_M}{\delta x_N} \end{bmatrix} \qquad (7.8)$$

The derivative of h($\tilde{x}$) cannot be obtained analytically, so it is calculated by getting small changes around $\{\tilde{x}\}$, i.e. h($\tilde{x}$ + Δx). The weight matrices can be varied as the iteration proceeds.

7.4 Application of Shirai's Method

A block diagram of the analysis procedure is shown in Fig 7.1. It comprises three main parts: an articulatory synthesis algorithm, a spectral estimation algorithm, and a minimization algorithm. The input speech, s(t), is analysed and its acoustic parameters, y, extracted. From an initial estimate, x, synthesis is carried out by the ASY synthesiser, using default glottal parameters, as was done in Chapter 6. The synthetic speech s'(t), the approximation to s(t), is analysed to extract its acoustic parameters, h($\tilde{x}$), using the CGI analysis of Chapter 5. These acoustic parameters are then compared to y using a specific error criterion, as discussed in the previous section. From this comparison, a new estimate of the articulatory parameters is obtained, and the iteration proceeds until the acoustic parameters of the model are sufficiently close to the real speech. The first two algorithms have been covered elsewhere, so the discussion here is mainly concerned with the minimization algorithm, and analysis considerations.

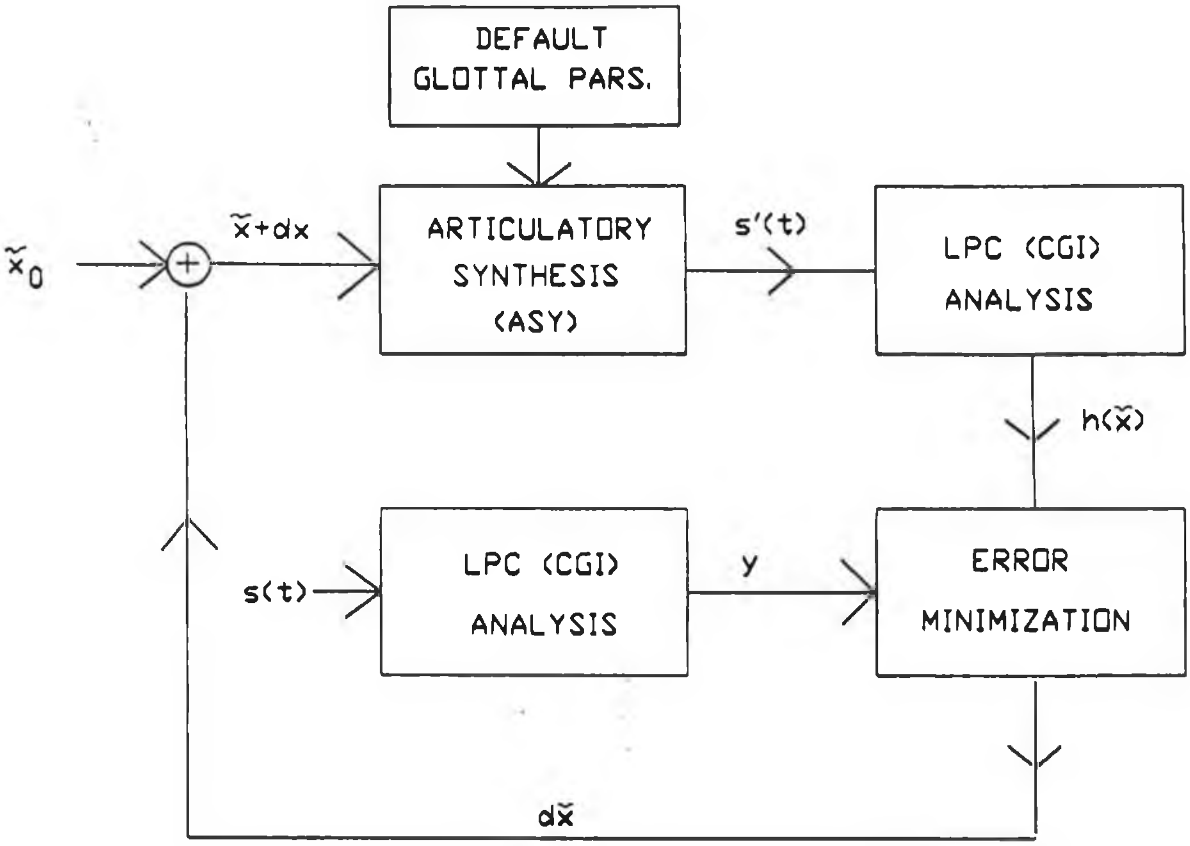


Fig 7.1 Adaptive Estimation Algorithm

7.4.1 Minimization Algorithm

The third section, the minimization algorithm, is basically an implementation of eqns. (7.5) and (7.6), i.e. the appropriate change in the articulatory parameters is computed, and they are then changed accordingly for the next iteration. For the implementation of this algorithm, various factors had to be considered.

7.4.1.1 Adaptation of Mermelstein's Model

The estimation algorithm was originally developed for Shirai's articulatory model [56]. This model, which is based on the statistical analysis of real data, automatically incorporates physiological and phonological constraints, making it possible to represent each articulatory position accurately using a minimum number of parameters. Only six parameters are used in all, compared to ten for the Mermelstein model.

Mermelstein's model, also developed from real X-ray data, should incorporate natural constraints, and therefore should be suitable for this type of analysis. In order to reduce the number of parameters, average values were taken for four parameters i.e. the hyoid (X and Y) coordinates, tongue tip length, and nasal parameter (velum). This was justified by the sensitivity analysis discussed in Chapter 6. In addition, the four extreme positions established for vowels in Chapter 6 were used as constraints, and the articulatory parameters were normalized with respect to these within the range $-1 \leq \tilde{x} \leq 1$. This normalization was done mainly because all the parameters of Shirai's model were bounded by unity. It also made it easier to see the deviation from the neutral condition (x=0), a condition of the minimization procedure, as well as helping to ensure that the articulatory parameters did not extend outside the admissable range. It also aided in the computation of the derivative of $h(\tilde{x})$, for determining a small change in $\{\tilde{x}\}$, and in the determination of the weighting matrices values.

7.4.1.2 Choice of Initial Estimate

In Shirai's method, the importance of an initial estimate is stressed, as the stability and speed of convergence are very much dependent on this. Apart from the first frame of speech, the initial estimate is taken as the estimate of the previous frame, which as well as being the most likely position, also ensures continuity in vocal tract shapes. For the first frame however, the starting value is obtained using a piecewise-linear estimate, obtained from regression analysis, as discussed in Section 7.2.1. For the ASY model here, it was decided to look up the linked codebook, generated in Section 6.7, to first find the closest acoustic match, according to the covariance measure, and then the corresponding articulatory position.

7.4.1.3 Choice of Weighting Matrices

From Shirai, the matrix R was taken as the identity matrix, to give equal weighting to each acoustic coefficient. The choice of the other two diagonal weighting matrices, Q and Γ, was somewhat arbitrary, but from examination of the values used for Shirai, it was decided to base them loosely around the relative sensitivity of each articulatory parameter. From Shirai, it was observed that, in general, the choice of weights corresponding to each parameter was inversely proportional to its sensitivity. For example, the N x N matrix Q is taken to be

$$Q = \begin{bmatrix} 0.125 & 0.0 & \cdots & & & 0.0 \\ 0.0 & 0.125 & & & & \\ \vdots & & 0.33 & & & \\ \vdots & & & 0.1 & & \\ \vdots & & & & 0.5 & \\ 0.0 & \cdots & & & & 0.25 \end{bmatrix} \qquad (7.9)$$

where the articulatory parameters are, in order, tongue centre, tongue angle, tongue tip angle, jaw, lip protrusion and lip height. The values correspond directly to the inverse of the number of increments used in Section 6.6.1 for computing the articulatory codebook. The matrix Γ, which weights the change in articulatory parameters between frames, is similarly derived, however it is given more emphasis than Q.

7.4.1.4 Computation of derivative of $h(\bar{x})$

As discussed earlier, the derivative of $h(\bar{x})$ cannot be obtained analytically.

Therefore, a small value of Δx was taken i.e. 0.01 (normalized). In addition, the derivative was taken so as to avoid extreme values, particularly as initial estimates were at the extremities for some articulatory parameters. Therefore, in order not to go outside the range, $\delta h(\tilde{x})$ was defined as

$$\delta h(\tilde{x}) = h(\tilde{x} + \Delta x) - h(\tilde{x}) \qquad -1 \leq \tilde{x} \leq 0 \qquad (7.10a)$$

and

$$\delta h(\tilde{x}) = h(\tilde{x}) - h(\tilde{x} - \Delta x) \qquad 0 \leq \tilde{x} \leq 1 \qquad (7.10b)$$

For each articulatory vector estimate, this derivative was computed for each direction in the articulatory space, and the corresponding change in each acoustic parameter was obtained, resulting in the MxN matrix of eqn. 7.8.

7.4.1.5 Choice of Acoustic Parameters

The acoustic parameters recommended by Shirai were the cepstrum coefficients as a change in the cepstrum coefficients is equivalent to a change in the log spectra, from their definition.

7.4.1.6 Convergence Criteria

The value of the convergence parameter is critical, as discussed above. As there were no strict guidelines, apart from a general limit of 1.0, it was decided to make it very small i.e. 0.05 initially, to avoid divergence and instability. As regards the definition of convergence, a value depending on the total mean squared error of the cepstrum coefficients was proposed, i.e. 0.1. Convergence was also governed by a maximum number of iterations i.e. 100.

7.5 Analysis Results and Possible Improvements

What is obvious from the preceding discussion is that there is a large number of choices and variables in this algorithm. It proved no trivial matter to establish optimum conditions for the convergence, and in fact no convergence could be obtained. This was not very surprising for many reasons.

Perhaps the most important factor is that the mean vocal tract length should be matched initially for each speaker. Methods for removing the effects of individual speakers have been proposed [56], which should be investigated. This normalization would also have an effect on the determination of the weighting matrices. A fairly large number and cross-section of speakers would be required to do this.

Another problem could be the acoustic distance measure used in the algorithm. In Chapter 6, it was found that the best possible distortion measure was the covariance measure. This would essentially involve replacing a weighting matrix with the variable covariance matrix, although a new algorithm would need to be derived, as this measure would not exactly fit in with its present form. Another idea, which would be easier to implement, would be the log area ratio measure, also recommended in Chapter 6.

The ratio of the acoustic to articulatory parameters, M:N, should also be considered. For uniqueness of solution, it is recommended that the number of acoustic parameters should exceed as much as possible that of the articulatory parameters. The current ratio is 8:6. By increasing the sampling rate, or alternatively by using linear combinations of the acoustic parameters, this ratio could be increased. In fact, Shirai used twelve cepstrum coefficients in his analysis.

Finally, it is obvious that an independent study of general convergence techniques, beyond the scope of the current research, would be very beneficial. Other algorithms exist, notably those of Charpentier [55], Levinson *et al.* [54] and Atal *et al.* [52]. Atal uses a table search, followed by optimization, similar to that proposed here. Levinson uses an unconstrained optimization, starting at the neutral shape. Using the neutral shape as an initial estimate was tried here, both for a general unconstrained optimization and the method described above. However, the results were no better. Charpentier, on the other hand, also uses a table search, but in the table construction, incorporates an analysis of curvature, and concentrates on the highly non-linear regions. This would be a possibility here, for obtaining a more accurate initial estimate, as it was found that the initial articulatory estimate was very dependent on the distortion measure used to extract it from the look-up table.

CHAPTER 8 DISCUSSION, IMPROVEMENTS AND CONCLUSIONS

8.1 Convergence Techniques

The complete implementation of an articulatory vowel vocoder is outside the scope of this thesis. The main reason for this is the difficulty encountered in the generation of an articulatory codebook using a training set of real speech. This involved using convergence techniques to solve the inverse problem of the vocal tract, as described in Chapter 7. Methods for improving the analysis in order to achieve convergence were already discussed extensively there, and will not be discussed here. However, it must be said that a large amount of data from various speakers would need to be analysed, in order to establish optimum conditions. Apart from the fact that this was not readily available, each iteration of the convergence requires a synthesis from an articulatory estimate, and a full CGI analysis. This is very computationally intensive, and would not be possible with available resources.

8.2 Bit Rates

The emphasis in this thesis has been on improving the quality of speech while still retaining low bit rates. Once a linked articulatory-acoustic codebook is generated, the number of bits required to represent each shape vector would be comparable to conventional coding of LPC parameters, i.e. for a codebook of say, 1024 shape vectors, 10 bits would be required. As the vocal tract changes slowly, the parameters would only need to be updated, for example, every third pitch frame, as already discussed in Chapter 5. As discussed in Section 6.9, the glottal parameters could be quite crudely quantized, say a maximum of 4 bits each, if scalar quantization was used. Assuming a parameter update every 20ms approximately, bit rates as little as 1200b/s could be achieved theoretically. Of course, the effect of vector quantization on speech quality would need to be investigated.

8.3 Resources and Computation

An example of the resources required for clustering can be seen in the work carried out by Schroeter *et al.* [], where it took 1000 hours of CPU time on a super-minicomputer to cluster 10,000 shapes, using the modified K-means algorithm. Sub-optimal solutions could also be found, for a lot less computation, but it is obvious that a huge amount of overall computation is required for the clustering and iteration processes. Fortunately, all this is only done on a once-off basis. More of a problem is the amount of computation involved in the CGI analysis. Methods for reducing this were discussed in Chapter 5, including the need to update the covariance matrix only one row at a time for sequential covariance analysis. Also, since the algorithm for extracting the closure region only examines the normalized mean squared error from the first half of the pitch frame, the sequential analysis does not need to be done for the whole frame, thus reducing computation considerably. The effect on quality of only analysing every third pitch frame for parameter extraction instead of picking the best of three could also be examined. All these factors contribute to making the vocoder a viable proposition. The possibility of converting ASY to run in real-time, should also be investigated.

8.4 Recording Conditions

A feature of any coder is that it should be robust. However, great care must be taken in recording speech for CGI analysis. A phase linear system is required, as otherwise the glottal waveform will be seriously degraded. The most serious degradation of results is caused by analogue tape distortion. This can be overcome by digitizing the speech directly, and with the advent of digital tapes, it may not be a problem in future. In addition, a low noise microphone with good low frequency resolution is required (e.g. an electret microphone). Ambient noise should be kept to a minimum.

Methods for compensating for phase distortion have been tried, with some success.

Veeneman *et al.* [57] used a prerecorded calibration signal to characterize the recording system, and hence design compensating filters. For analysing the true effect of distortion on both the glottal waveform and the transfer function obtained, equipment is required which would record the glottal opening and closing, e.g. an electroglottograph, (EGG).

8.5 Sampling Rate

The advantages of using a higher sampling rate, e.g. 10Khz, for articulatory coding were already discussed in Chapters 6 and 7. Increasing the sampling rate should also help the CGI analysis, as there will be more speech samples in the closed glottis interval. Thus, the analysis interval length could also be increased, which would in turn increase stability, as in general, the longer the interval for covariance analysis, the less likelihood of instability. This would be particularly useful in areas of slight constriction in the vocal tract, where the CGI analysis would not be expected to work as well, as the assumption of plane wave propogation is not as justified.

8.6 Limitations of CGI / Alternatives

Due to the sensitivity of the CGI analysis to the recording conditions, its accepted failure for high pitched voices (not enough samples in the closed glottis interval), and also the larger amount of computation involved in comparison to conventional LPC techniques, it is felt that more research should be done into adaptive inverse filtering techniques. These techniques would also be more adaptable to other types of speech sounds than the CGI analysis. However, it was seen that currently there is a wide difference in results obtained from the two classes of methods, the CGI analysis being far superior. While it would be expected that CGI analysis would extend easily to semivowels (i.e. liquids, such as /w/ and /l/, and glides, such as /r/ and /y/), which are essentially voiced sounds, there is no way it would work for consonants. A possibility would be to include some sort of binary voicing decision at the speech input to decide if CGI analysis is appropriate. Then unvoiced sounds could be dealt with using a different analysis.

8.7 Completion of the Articulatory Vocoder

As mentioned in Section 8.1, the main task still outstanding is to perfect the convergence technique used to extract the articulatory parameters from the speech wave. The next step is clustering of the resulting articulatory shapes, using a reliable algorithm, followed by the generation of a glottal codebook in a similar manner. Once the codebooks are completed, the overall quality can be assessed, and the suitability of the proposed covariance distortion measure evaluated.

8.8 Conclusions

An investigation into articulatory vocoding was carried out in this thesis. In Chapter 2, the articulatory mechanism of speech production was described in detail, along with a description of the articulatory synthesiser to be used in the research. This was followed in Chapter 3 by an acoustic tube model representation of the vocal tract, and its corresponding transfer function was derived, using Portnoff's equations. In Chapter 4 an investigation into Linear Predictive Coding, a time domain method, which is now the most popular of speech analysis methods, was carried out. Various methods of LPC were compared, and algorithms for the solution of the autocorrelation and covariance method presented. Using the lattice method, a correlation between the reflection coefficients of LPC and those of the acoustic tube model was derived.

The above results were used in Chapter 5, where methods of extracting the vocal tract shape from the speech wave were investigated. These methods were primarily based on modifications of the LPC technique, and were concerned with removing the glottal and radiation characteristics which are not removed by standard LPC. Algorithms were first presented for the autocorrelation method, using four different types of preemphasis. Three types were asynchronous methods, i.e. first order preemphasis, adaptive first order preemphasis and adaptive multi-order preemphasis. The last was a pitch synchronous method, based on detecting glottal closure. The methods were compared by applying glottal inverse filtering to the vocal tract transfer function obtained. The glottal waveform extracted was examined to see how closely it resembled a smooth idealized pulse, an indication of the analysis accuracy. Of all these autocorrelation based preemphasis methods, it was shown that the best results were obtained for the straight-difference first order method, as all the rest were found to impose too much preemphasis.

The second type of method was based on the covariance method of LPC, known as CGI analysis, and was based on the detection of the closed glottis interval using the normalized mean squared error obtained from sequential covariance analysis. Drawbacks with existing methods were illustrated, and a new robust algorithm for detecting the appropriate location was derived, from close examination of the error waveforms. A method for extracting the glottal parameters from the glottal waveform was also presented. It was shown that, in all cases, the CGI method yielded superior results to the first order preemphasis autocorrelation method. This was apparent in both the glottal waveforms extracted,and the values of the bandwidths obtained. The smaller CGI bandwidths agreed more with general trends of measured bandwidths [28].

The CGI method was used in Chapter 6 for the acoustic analysis part of the articulatory vocoder. In this Chapter, the concept of a linked codebook of articulatory-acoustic parameters was introduced, and two methods for generating such a codebook were proposed, one based on synthetic speech, and one based on real speech. An evaluation of suitable distortion measures was carried out in the acoustic domain, and it was decided that the best distortion measure to use was a covariance measure, proposed here as a modification of the existing Itakura-Saito measure for the autocorrelation method of LPC. The disadvantages of using an articulatory codebook derived from synthetic speech were discussed, and a method for constructing one based on real speech was proposed.

To construct an articulatory codebook from real speech, a method is required which extracts articulatory parameters from the speech wave. Chapter 7 investigated an algorithm developed by Shirai for this purpose, and modified it for the ASY model. As useful results were not obtained from the algorithm, the difficulties of such an analysis were detailed. Various improvements were suggested, which if implemented, should eventually result in a robust algorithm.

To conclude, this thesis proposed an accurate method of extracting useful acoustic parameters from the speech wave, for use in an articulatory vocoder. A full design for an articulatory vocoder, with the articulatory codebook based on synthetic speech, was presented. The need to improve on the estimation of articulatory parameters from the speech wave was stressed, in order to generate a codebook from a training set of real data.

REFERENCES

1. J.N. Holmes, "Formant synthesisers - Cascade or Parallel", **Speech Comm.**, Vol. 2, pp. 251-273.

2. B.S. Atal and M.R. Schroeder, "Adaptive Predictive Coding of Speech Signals", **Bell Syst. Tech. J.**, Vol 49, pp. 1973-1987, Oct. 1970.

3. J.L. Flanagan, **"Speech Analysis, Synthesis and Perception"**, New York: Springer Verlag, 1972.

4. M. Sondhi and J. Schroeder, "A Non-Linear Articulatory Speech Synthesiser using both Time and Frequency domain elements", **Proc. IEEE ICASSP**, Tokyo, Japan, Vol. 3, pp. 1999-2002, 1986.

5. F. Fallside and W. Woods, **"Computer Speech Processing"**, Englewood Cliffs, New Jersey: Prentice Hall 1985.

6. D.H. Klatt, "Synthesis by Rule of Consonant-Vowel Syllables", **Speech Comm. Group Working Papers**, Vol. 3, MIT, Cambridge, MA, pp. 93-104.

7. K. Ishizaka and J.L. Flanagan, "Synthesis of Voiced Sounds from a Two Mass Model of the Vocal Cords", **Bell Syst. Tech. J.**, Vol 51(6), pp. 1233-1268, 1972.

8. H. Wakita and G. Fant, "Towards a better Vocal Tract Model", **Speech Transmission Lab. Quarterly Progress and Status Report, (STL-QPSR)**, Vol. 1, RIT, Stockholm, Sweden, pp. 9-29 1978.

9. J.L. Flanagan and L. Landgraf, "Self oscillating source for Vocal Tract Synthesisers", **IEEE Trans. Audio and Electroacoust.**, Vol AU-16, pp. 57-64, 1968.

10. H. Fujisaka and M. Ljungvist, "Proposal and evaluation of models for the glottal source waveform", **Proc. IEEE ICASSP,** pp. 1605-1608, Tokyo 1986.

11. K.N. Stevens and A.S. House, "Development of a quantitative description of vowel articulation", **JASA**, Vol. 27, pp 484-493, 1955.

12. G. Fant, "**Acoustic Theory of Speech Production",** Mouton, The Hague, 1970.

13. J.L. Kelly and C. Lochbaum, "Speech Synthesis", **Proc. Stockholm Speech Comm. Seminar,** RIT, Stockholm, Sweden, September 1962.

14. C.H. Coker, "A Model of Articulatory Dynamics and Control", **Proc. IEEE** Vol. 64, No. 4, pp. 451-460, April 1976.

15. P. Mermelstein, "Articulatory Model for the study of Speech Production", **JASA** Vol. 53, No. 4, pp. 1070-1082, 1973.

16. P. Rubin, T. Baer and P. Mermelstein, "An Articulatory Synthesiser for Perceptual Research", **Haskins Lab. Status Report on Speech Research",** SR-57, pp. 1-16, 1979.

17. J.S. Perkell, "**Physiology of Speech Production: Results and Implications of a Quantitative and Cineradiographic Study",** MIT, Cambridge, MA, 1969.

18. A.E. Rosenberg, "Effect of glottal pulse shape on the quality of natural vowels", **JASA** Vol. 49, No. 2, Part 2, pp. 583-590, 1971.

19. M.R. Portnoff, "A Quasi-One-Dimensional Digital Simulation for the time-varying Vocal Tract", **M.S. Thesis,** Dept. of Electrical engineering, MIT, Cambridge, MA, June 1973.

20. H. Wakita, "Direct Estimation of the Vocal Tract Shape by Inverse Filtering of Acoustic Speech Waveforms", **IEEE Trans. Audio and Electroacoust.,** Vol. 21, No. 5, pp. 417-427, Oct. 1973.

21. J.D. Markel and A.H. Gray Jr., **"Linear Prediction of Speech"**, New York, NY : Springer Verlag, 1976.

22. J. Makhoul, "Linear Prediction: A Tutorial Review", **Proc. IEEE**, Vol. 63, pp. 561-580, April 1975.

23. B.S. Atal and S.L. Hanauer, "Speech Analysis and Synthesis by Linear Prediction of the speech wave", **JASA**, Vol. 50, pp. 637-655, 1971.

24. J. Makhoul, "Stable and Efficient methods for Linear Prediction", **IEEE Trans. ASSP**, Vol. 25, No. 5, pp. 423-428, Oct. 1977.

25. J. Durbin, "The Fitting of Time Series Models", **Rev. Int'l. Statist. Inst.**, Vol 28, pp. 233-244, 1960.

26. N. Levinson, "The Wiener RMS Error Criterion in Filter Design and Prediction", **J. Math. Phys.**, Vol.25, pp.261-278, 1947.

27. A.V. Oppenheim and R.W. Schafer, **"Digital Signal Processing"**, Englewood Cliffs, New Jersey : Prentice Hall, 1975.

28. L.R. Rabiner and R.W. Schafer, **"Digital Processing of Speech Signals"**, Englewood Cliffs, New Jersey : Prentice Hall, 1971.

29. B.S. Atal, "Determination of the Vocal Tract Shape directly from the Speech Wave", **JASA**, Vol. 47 (A), p. 64, Jan. 1970.

30. T. Nakajima, H. Omura and S. Ishizaki, "Estimation of Vocal Tract Area Functions by Adaptive Inverse Filtering Methods and Identification of Articulatory Model", **Proc. Speech Comm. Seminar**, Stockholm, John Wiley and Sons. 1974.

31. S. Murphy, University of Ulster, Jordanstown, Belfast, (Direct communication).

32. D.Y Wong, J.D. Markel and A.H. Gray, "Least squares glottal inverse filtering from the acoustic speech waveform", **IEEE Trans. ICASSP,** Vol. 27, No. 4, pp. 350-355, Aug. 1979.

33. H.W. Strube, "Determination of the instant of glottal closure from the speech wave", **JASA,** Vol. 56, No. 5, pp. 1625-1629, 1974.

34. B.S. Atal and M.R. Schroeder, "Predictive Coding of Speech Signals and Subjective Error Criteria", **IEEE Trans. ASSP,** Vol. 27, No. 3, June 1977.

35. J.N. Larar, Y.A. Alsaka and D.G. Childers, "Variability in Closed Phase Analysis of Speech", **Proc. IEEE ICASSP,** pp. 1089-1092, 1985.

36. I. Mallawany, "Area Function extraction over the closed glottal interval", **Articulatory Modelling Symposium,** Grenoble, July 1977.

37. H.W Strube, "Can the Area Function of the Human Vocal Tract be determined from the Speech Wave? ", **U.S - Japan Joint Seminar on Dynamic Aspects of Speech Production,** Tokyo University Press, pp. 279-302, 1977.

38. P. Hedelin, "A glottal LPC vocoder", **Proc. IEEE ICASSP,** pp. 6-10, 1984.

39. J.N. Holmes, "Formant Excitation before and after Closure", **Proc. IEEE ICASSP,** pp. 39-42, April 1976.

40. A.S. Anath, D.G. Childers and B. Yegnanarayana, "Measuring source - tract interaction from speech", **Proc. IEEE ICASSP,** pp.1093-1096, 1985.

41. B. Cramen and L. Boves, "Aerodynamic Aspects of Voicing: Glottal Pulse Skewing Revisited", **Proc. IEEE ICASSP,** pp. 1093-1096, 1985.

42. R.M. Gray, "Vector Quantization", **IEEE ASSP Magazine,** April 1984.

43. J. Makhoul, "Vector Quantization in Speech Coding", **Proc. IEEE,** Vol. 73, No. 11, Nov. 1985.

44. Y. Linde, A. Buzo and R.M. Gray, "An Algorithm for Vector Quantizer Design", **IEEE Trans. Commun.,** Vol. 28, No. 1, pp.84-95, Jan. 1980.

45. A. Buzo, A.H. Gray, R.M. Gray and J.D. Markel, "Speech Coding based on Vector Quantization", **IEEE Trans. ASSP,** Vol. 30, No. 2, pp. 294-303, April 1982.

46. S. Saito and K. Nakata, **"Fundamentals of Speech Signal Processing",** Florida: Academic Press 1985.

47. K. Shirai and T. Kobayashi, "Estimating Articulatory Motion from Speech Wave", **Speech Comm.** 5, pp.159-170, 1986.

48. F. Itakura, "Minimum Prediction Residual Principle Applied to Speech Recognition", **IEEE Trans. ASSP,** Vol. 23, No. 1, pp. 67-72, Feb. 1975.

49. J. Schroeter, J.N. Larar and M.M. Sondhi, "Speech Parameter Estimation using a Vocal Tract / Cord Model", **Proc. IEEE ICASSP,** pp. 308-311, 1987.

50. R. Kuc, F. Tuteur and J.R. Vaisnys, "Determining Vocal Tract Shape by Applying Dynamic Constraints", **Proc. IEEE ICASSP,** pp. 1101-1104, 1985.

51. B.S. Atal, "Towards Determining Articulator Positions From the Speech Signal", **Speech Comm. Seminar,** Stockholm, Sweden, pp. 1-9, Aug. 1974.

52. B.S. Atal, J.J. Chang, M.V. Matthews and J.W. Tukey, "Inversion of articulatory-to-acoustic transformation in the Vocal Tract by a Computer Sorting Technique", **JASA,** Vol. 63, No. 5, pp. 1535-1550, May 1978.

53. M. Sondhi and J.R. Resnick, "The inverse problem of the Vocal Tract: Numerical Methods, Acoustical Experiments, and Speech synthesis", **JASA,** Vol. 73, No. 3, pp. 985-1002, March 1983.

54. S.E. Levinson and C.E. Schmidt, "Adaptive Computation of Articulatory Parameters from the Speech Signal", **JASA,** Vol. 74, No. 4, pp. 1145-1154, Oct. 1983.

55. F. Charpentier, "Determination of the Vocal Tract Shape from the formants by analysis of the Articulatory-to-Acoustic Non-Linearities", **Speech Comm.,** Vol. 3, pp. 291-308, 1984.

56. K. Shirai and M. Honda, "Estimation of Articulatory Motion from Speech Waves, and its application to Automatic Recognition", **Spoken Language Generation and Understanding,** pp. 87-99, : D. Reidel Publishing Co., 1980.

57. D.E. Veeneman and S.L. BeMent , "Automatic glottal inverse filtering from speech and electographic signals", **IEEE Trans. ASSP,** Vol. 33, No. 2, April 1985.