CONTINUOUS ADAPTATION OF LINEAR MODELS WITH IMPULSIVE EXCITATION

S. W. Beet and L. Baghai-Ravary

Department of Electronic and Electrical Engineering,
University of Sheffield, Mappin Street, Sheffield, S1 3JD, UK.

ABSTRACT

This paper presents a new approach to continuously-adaptive system modelling, designed for the analysis of autoregressive (AR) systems excited by signals including an impulsive component. Voiced speech is well represented by such a model, and is used to demonstrate the advantages of the new approach. These include:

1. AR model parameter estimates are more stable in the region of pitch events.

2. A faster adaptation rate can be used, reducing the recovery time after plosives or other sudden changes in signal statistics.

The new method is based on multiple simultaneous estimates of each sample, using separate but related estimators. The general concept is illustrated here using a linear prediction (LP) approach to continuously-adaptive autoregressive (AR) modelling, based on the least mean square (LMS) algorithm.

1. INTRODUCTION

In many applications it is unsatisfactory to treat speech as a piecewise-stationary signal. This precludes the use of frame-based analyses to characterise the signal, and so some form of continuously-varying parameterisation is desired.

A common approach is to use a gradient descent algorithm to improve the accuracy of the parameterisation incrementally as each new sample becomes available [1, 2]. These methods generally assume that the the vocal apparatus is driven by a stationary, stochastic signal. This is quite accurate during those periods when the vocal folds are closed [3], but is quite unrealistic at the moments of opening and closure.

Consequently, the parameters yielded by traditional versions of this method exhibit undesirable perturbations, especially at the onset of each pitch pulse. At this point, the high value of the prediction error causes the estimated model parameters to change rapidly (even though the vocal tract transfer function is only changing slowly). To minimise these problems, the convergence rate of the adaptation algorithm is generally set much lower than could otherwise be possible [4].

The linear prediction approach to continuously adaptive system modelling is exemplified by the LMS algorithm. Firstly, a weighted sum of previous signal values is formed:

$$\hat{x}_n = \sum_{m=1}^{M} a_m x_{n-m} \tag{1}$$

where x_n is the n^{th} input value, a_m is the m^{th} prediction coefficient, and $\hat{x}_n$ is the predicted value of x_n. The error is then calculated:

$$e_n = x_n - \hat{x}_n = x_n - \sum_{m=1}^{M} a_m x_{n-m} \tag{2}$$

The sequence $e[n]$ then forms the residual signal, whose power is minimised by successive application of the LMS steepest descent update rule:

$$\begin{aligned} a_m &\leftarrow a_m - \mu \frac{\partial e_n^2}{\partial a_m} \\ &= a_m - 2\mu\, e_n \frac{\partial e_n}{\partial a_m} \\ &= a_m + 2\mu\, e_n x_{n-m} \end{aligned} \tag{3}$$

In these equations, μ deterimines the speed of convergence, and is chosen according to the properties of the data. Too small a value, and the system will only adapt very slowly; too large a value and the adaptation will not converge.

2. THE FORWARD-BACKWARD MINIMUM ERROR METHOD

The conventional LMS approach described in equations 2 and 3 can be badly affected by outliers in the sample distribution of the stochastic process assumed to be driving the AR system. If an impulse is present in the data, it will cause a large error, which will then be prolonged by the infinite-duration impulse response of the AR system under consideration. That error will give rise to a sudden change in the predictor coefficients, in an attempt to model it as part of the AR transfer function.