CHAPTER 6. CONCLUSION AND FURTHER RESEARCH

6.1. Conclusion

The *Cascade RLS with subsection adaptation* (CRLS-SA) algorithm has been proposed to reduce the computational requirements of the *recursive-least squares* (RLS) algorithm for linearly predicting the coefficients of an AR process, where each section in the CRLS-SA is a second order filter. The computational reduction is obtained by using only the 2x2 diagonal components of the gradient auto-correlation matrix for adapting the coefficients. This can be done because for linear prediction (LP) applications, the gradients of a section tend to be uncorrelated with the gradients of other sections.

The CRLS-SA algorithm turns out to converge faster than the direct form RLS. The analysis shows that the DeBrunner-Beex conjecture, which states that a structure having a smaller convergence time constant converges faster than a structure with a larger convergence time constant, is satisfied. The CRLS-SA structure is shown to have a smaller convergence time constant than the direct form, and - in fact - a much smaller one when the poles of the AR process are closely spaced.

CRLS-SA has been used for linear prediction, frequency estimation and tracking, and direct adaptive LSF estimation and synthesis including vector quantization of the LSF. The results for LP applications show that CRLS-SA performs better than the auto-correlation method in terms of deviations from the original system, as measured by the Itakura distance. Direct adaptive LSF computation using CRLS-SA yields less computational complexity than the autocorrelation approach because there is no need to do root finding. A split VQ is used to quantize the LSF_2, because the LSF_2 of each section in CRLS-SA are independent of the LSF_2 of other sections. The use of CRLS-SA for estimating frequencies shows good results. Also, by using the down-sampling technique, CRLS-SA can be used to estimate (very) low frequencies.

6.2. Further Research

Since in the CRLS-SA algorithm the off-diagonal components of the gradient auto-correlation matrix are ignored, it will be of interest to study its effects during convergence as well as steady state. The off-diagonal components tend to be small at steady state. This does not mean that during initial convergence these values are also small. Hence there could be some effect on the initial convergence rate. However, we have seen that CRLS-SA tends to converge faster than the direct form RLS, in which the off-diagonal values are used. A more complete answer to what the effect is of ignoring the off-diagonal terms during initial convergence remains to be found.

It will be interesting to see whether ignoring the off-diagonal values causes some bias at steady state. Recall that the bias in the LSF was smaller with CRLS-SA than with the autocorrelation method, so that - for speech purposes at least – any such bias seems tolerable.

The split VQ for quantizing the LSF_2 yields a very good result. The spectral distortion meets the transparency requirements, and the SSNR of the processed speech synthesized using split VQ(2,4,4) is better than that for MNRU Q 40.