A MODEL FOR AN ARMA PROCESS SPLIT IN SUB-BANDS

Luiz W. P. Biscainho, Paulo S. R. Diniz and Paulo A. A. Esquef

DEL/EE & PEE/COPPE, UFRJ Caixa Postal 68504 - Rio de Janeiro, RJ, Brazil CEP: 21945-970 {wagner,diniz, esquef}@lps.ufrj.br

ABSTRACT

This work proposes a model, originated from the power spectral density concept, for the sub-band processes obtained by analysis of an ARMA process by a decimating filter bank. As an example, the model for an AR process analyzed in octaves by a tree-structured FIR filter bank is derived in a recursive way, and some interpretations are given.

1. INTRODUCTION

Multi-rate digital processing [1] is today a well-established topic, extensively applied in communications, image and audio industry and other areas, for signal coding, adaptive or statistical processing etc.

A special class of discrete random processes [2] are those obtained by passing white-noise through a linear digital filter—called Moving-Average (MA) for an Finite-Impulse-Response (FIR) filter, Autoregressive (AR) for an all-pole filter or Autoregressive-Moving-Average (ARMA) in the general case.

Many applications in speech and audio employ these processes as models. This is particularly true for audio restoration [3], where ARMA and AR processes play an important role in description of signals. In this context, model-based processing in sub-bands would profit from a similar description of the sub-band signals, if it was possible. This is the motivation behind this work.

This work uses polyphase decomposition of systems [1] and power spectral density of random signals [2] to get a simple model that describes sub-band signals resulting from the analysis of an ARMA process by a decimating filter bank. The special case of an AR process passing through an octave-band filter bank is also detailed, leading to some useful interpretations.

Applications of these results to audio modeling and restoration will appear in future works [4]. Practical simulations yield good results.

The paper is organized as follows. Section 2 covers the general case of the ARMA process divided in N bands, Section 3 derives and discusses the case of the AR process divided in octaves and Section 4 summarizes the results.

2. GENERAL MODEL: ARMA PROCESS IN N BANDS

The purpose of this Section is to derive a simple low-rate model for the signals that results from the analysis of an ARMA process in sub-bands. First, consider the N-band multi-rate system shown in Fig. 1, which analyzes the ARMA process s(k) defined by

$$s(k) = \sum_{i=1}^{J} a(i)s(k-i) + \sum_{j=0}^{J} b(j)e(k-j).$$

$$F_{0}(z) \longrightarrow N \longrightarrow s_{0}(l)$$

$$F_{1}(z) \longrightarrow N \longrightarrow s_{1}(l)$$

$$F_{1}(z) \longrightarrow N \longrightarrow s_{1}(l)$$

$$F_{N-1}(z) \longrightarrow N \longrightarrow s_{N-1}(l)$$

Figure 1: ARMA Process analyzed by an *N*-band decimating filter bank.

To obtain the model, we can follow the steps depicted in Fig. 2.

- (a) Consider the subsystem corresponding to a given sub-band n.
- (b) Represent s(k) explicitly as the adequate IIR filter fed by a white-noise process e(k). Group this filter and the analysis filter F_n(z) into F̂_n(z).
- (c) Obtain a polyphase representation for $\hat{F}_n(z)$.
- (d) Place the decimator before the adder.
- (e) For each polyphase p, place the decimator before the filter $\hat{F}_{np}(z)$, and represent the respective component of e(k) explicitly as $e_p(l)$.
- (f) Being σ_e^2 the variance of e(k), it is easy to conclude that $e_p(l)$, for p = 0, 1, ..., N-1, are mutually uncorrelated white-noise processes with variances

$$E[e_p^2(l)] = E[e^2(Nl+p)] = E[e^2(k)] = \sigma_e^2$$

Since the signals $s_{np}(l)$, for p = 0, 1, ..., N-1, are colored versions of $e_p(l)$, respectively, they are also mutually uncorrelated. Then, the autocorrelation of $s_n(l)$ can be written without cross-terms as

$$R_{s_n s_n}(\Delta) = \sum_{p=0}^{N-1} R_{s_n p s_n p}(\Delta)$$





Figure 2: Generation of $s_n(l)$: from the multi-rate representation to a low-rate model.

leading to the power spectral density

$$\begin{aligned} S_{s_n s_n}(z) &= \sum_{p=0}^{N-1} S_{s_n p s_n p}(z) = \\ &= \sum_{p=0}^{N-1} \hat{F}_{n p}(z) \hat{F}_{n p}(z^{-1}) \sigma_e^2 = S_{s_n s_n}(-z). \end{aligned}$$

By applying factorization to the expression above,

$$\mathcal{S}_{s_n s_n}(z) \stackrel{\Delta}{=} \hat{F}_{d_n}(z) \hat{F}_{d_n}(z^{-1}) \sigma_e^2,$$

we can get a representation of $\tilde{s}_n(l)$ —equivalent to $s_n(l)$ in terms of its power spectral density—as an ARMA process defined by the minimum-phase filter $\hat{F}_{d_n}(z)$ fed by a white-noise process with variance σ_e^2 , denoted as $e_{d_n}(l)$.

Now, a complete equivalent model would consist of N similar subsystems in parallel. However, this model does not express the mutual correlation between different sub-bands. In the following, we obtain such a description.

Consider 2 distinct sub-bands n_1 and n_2 , each one described as in Fig. 2(e). The cross-correlation between their signals is given by

$$\begin{aligned} R_{s_{n_1}s_{n_2}}(\Delta) &= \sum_{p=0}^{N-1} E[s_{n_1p}(l)s_{n_2p}(l+\Delta)] \\ &= \sum_{p=0}^{N-1} E[(\hat{f}_{n_1p} * e_p)(l)(\hat{f}_{n_2p} * e_p)(l+\Delta)], \end{aligned}$$

resulting in the cross-power spectral density

$$S_{s_{n_1}s_{n_2}}(z) = \left[\sum_{p=0}^{N-1} \hat{F}_{n_1p}(z)\hat{F}_{n_2p}(z^{-1})\right]\sigma_e^2$$

3. MODEL FOR AN AR PROCESS IN OCTAVES

In this section, we apply the results from Section 2 to a usual situation in audio applications: an AR process split in octaves. This special case leads to some useful interpretations.

3.1. Model derivation

Start from the order-I autoregressive process

$$s(k) = \sum_{i=1}^{I} a(i)s(k-i) + e(k),$$

where e(k) is white-noise with variance σ_e^2 .

Consider the binary-tree structured FIR filter bank depicted in Fig. 3, used to analyze s(k) in octaves.



Figure 3: Analysis of an AR process by an octave-band decimating filter bank.

In each stage, the analysis filters are the high-pass $F_H(z)$ and the low-pass $F_L(z)$, both of order Q. After m stages, there will be m + 1 sub-bands, from $s_1(k_1)$ to $s_m(k_m)$ besides $\hat{s}_m(k_m)$. Now, we obtain the polyphase representation for each sub-band. Concerning the first stage, we have

$$\frac{F_H(z)}{A(z)} = \frac{F_H(z)A(-z)}{A(z)A(-z)} \triangleq \frac{B_H(z)}{A_1(z^2)} \triangleq \frac{B_{10}(z^2) + z^{-1}B_{11}(z^2)}{A_1(z^2)}$$

and

$$\frac{F_L(z)}{A(z)} = \frac{F_L(z)}{A(z)} \frac{A(-z)}{A(-z)} \stackrel{\triangle}{=} \frac{B_L(z)}{A_1(z^2)} \stackrel{\triangle}{=} \frac{\hat{B}_{10}(z^2) + z^{-1}\hat{B}_{11}(z^2)}{A_1(z^2)}.$$

These expressions, along with the transformations shown in Fig. 4, describe the polyphase model that leads to $s_1(k_1)$ and $\hat{s}_1(k_1)$. Note that the generation of $s_1(k_1)$ has been omitted from the figure for reasons of space.



Figure 4: Generation of $\hat{s}_1(k_1)$ —polyphase representation.

Starting with $\hat{s}_1(k_1)$, we proceed to the second stage,

$$\begin{split} F_{H}(z)\frac{\dot{B}_{10}(z)}{A_{1}(z)} &= F_{H}(z)\frac{\dot{B}_{10}(z)}{A_{1}(z)}\frac{A_{1}(-z)}{A_{1}(-z)} \stackrel{\triangle}{=} \\ &\stackrel{\triangle}{=} \frac{B_{10H}(z)}{A_{2}(z^{2})} \stackrel{\triangle}{=} \frac{B_{20}(z^{2}) + z^{-1}B_{22}(z^{2})}{A_{2}(z^{2})}, \\ F_{H}(z)\frac{\dot{B}_{11}(z)}{A_{1}(z)} &= F_{H}(z)\frac{\dot{B}_{11}(z)}{A_{1}(z)}\frac{A_{1}(-z)}{A_{1}(-z)} \stackrel{\triangle}{=} \\ &\stackrel{\triangle}{=} \frac{B_{11H}(z)}{A_{2}(z^{2})} \stackrel{\triangle}{=} \frac{B_{21}(z^{2}) + z^{-1}B_{23}(z^{2})}{A_{2}(z^{2})}, \\ F_{L}(z)\frac{\dot{B}_{10}(z)}{A_{1}(z)} &= F_{L}(z)\frac{\dot{B}_{10}(z)}{A_{1}(z)}\frac{A_{1}(-z)}{A_{1}(-z)} \stackrel{\triangle}{=} \\ &\stackrel{\triangle}{=} \frac{B_{10L}(z)}{A_{2}(z^{2})} \stackrel{\triangle}{=} \frac{\dot{B}_{20}(z^{2}) + z^{-1}\dot{B}_{22}(z^{2})}{A_{2}(z^{2})} \end{split}$$

and

$$F_L(z)\frac{\hat{B}_{11}(z)}{A_1(z)} = F_L(z)\frac{\hat{B}_{11}(z)}{A_1(z)}\frac{A_1(-z)}{A_1(-z)} \stackrel{\triangle}{=} \\ \stackrel{\triangle}{=} \frac{B_{11L}(z)}{A_2(z^2)} \stackrel{\triangle}{=} \frac{\hat{B}_{21}(z^2) + z^{-1}\hat{B}_{23}(z^2)}{A_2(z^2)}.$$

These expressions, along with the transformations shown in Fig. 5, describe the polyphase model that leads to $s_2(k_2)$ and $\hat{s}_2(k_2)$. Note that the generation of $s_2(k_2)$ has been omitted from the figure for reasons of space.



Figure 5: Generation of $\hat{s}_2(k_2)$ —polyphase representation.

After a general *m*-th stage, one can obtain the polyphase representation of the system that generates signals $s_m(k_m)$ and $\hat{s}_m(k_m)$, shown in Fig. 6.

Referring to the general sub-band signal s_m , the same reasoning



Figure 6: Generation of $s_m(k_m)$ and $\hat{s}_m(k_m)$ —polyphase representation.

applied in Section 2 leads to the power spectral density

$$S_{s_m s_m}(z) = \frac{\sum_{p=0}^{2^m - 1} B_{mp}(z) B_{mp}(z^{-1})}{A_m(z) A_m(z^{-1})} \sigma_e^2 \triangleq \\ \stackrel{\Delta}{=} \frac{B_m(z)}{A_m(z)} \frac{B_m(z^{-1})}{A_m(z^{-1})} \sigma_e^2.$$

In conclusion, as illustrated in Fig. 7, we described $\tilde{s}_m(k_m)$ —equivalent to $s_m(k_m)$ in terms of its power spectral density—as an ARMA process defined by the minimum-phase filter

$$\mathcal{M}_m(z) \stackrel{\triangle}{=} \frac{B_m(z)}{A_m(z)}$$

fed by a white-noise process, denoted as $e_{d_m}(k_m)$, with variance σ_e^2 .

$$e_{d_m}(k_m) \circ \longrightarrow \boxed{\frac{B_m(z)}{A_m(z)}} \longrightarrow \widetilde{s}_m(k_m)$$

Figure 7: Model for the signal in sub-band *m*.

Completing the model, the cross-power spectral density between same rate sub-bands can also be written as

$$S_{\hat{s}_m s_m}(z) = \frac{\left[\sum_{p=0}^{2^m - 1} \hat{B}_{mp}(z) B_{mp}(z^{-1})\right]}{A_m(z) A_m(z^{-1})} \sigma_e^2$$

3.2. Comments

We can draw some conclusions and speculations after the model filters of individual sub-bands. First, it is possible to deduce that the numerator and denominator orders of $\mathcal{M}_m(z)$ are

 $\begin{cases} O_{\text{num}}(m+1) = \lceil \frac{O_{\text{num}}(m)+I}{2} \rceil, \ m \ge 1 \\ O_{\text{num}}(1) = \lceil \frac{Q+I}{2} \rceil \end{cases} \text{ and } O_{\text{den}}(m) = I, \text{ re-}$

spectively, except for possible canceled terms.

Furthermore, the location of the model filter poles after each stage can be exactly predicted. From stage m to stage m + 1, the denominator of the model filter transfer function is calculated by

$$A_{m+1}(z^2) = A_m(z)A_m(-z)$$

If we suppose, e.g.,

$$A_m(z) = 1 - 2r\cos\theta z^{-1} + r^2 z^{-2},$$

it can be shown that

$$A_{m+1}(z) = 1 - 2r^2 \cos(2\theta) z^{-1} + (r^2)^2 z^{-2}.$$

This can be generalized to any number of poles and means that each stage squares the value of the model filter poles; so, each complex natural mode has its frequency doubled and its associated selectivity reduced.

Mapping the model filter zeros is a more difficult task, as it results from successive compositions of modified versions of the original model denominator A(z) with the analysis filters. What can be said is that the increasing selectivity resulting from the successive filtering stages should gradually "eliminate" the effect of some modes; another way to visualize this fact is consider that there are zeros canceling poles in the model transfer function. As a consequence, one expects the model orders to be reduced along the stages. This is an interesting issue, because it allows the use of lower-order approximate models for sub-bands. Simulations have confirmed this expectations [4].

4. SUMMARY

A low-rate model for the sub-band signals that result from passing an ARMA process through a multi-rate system was proposed. The model, equivalent in terms of the power spectral density, consists of one ARMA process per sub-band. After examination of the correspondent results for an AR process analyzed by an octave-band filter bank, some useful interpretations were drawn, which suggest the use of reduced-order sub-band models. Future works will present applications of these results in audio processing.

5. REFERENCES

- P. P. Vaidyanathan, *Multirate Systems and Filter Banks*, chapter 4, pp. 100–133. Englewood Cliffs, NJ, USA: Prentice-Hall, 1993.
- [2] A. Papoulis, Probability, Random Variables and Stochastic Processes, section 10.4, pp. 332–336. New York, NY, USA: McGraw-Hill, 3 ed., 1991.
- [3] S. J. Godsill and P. J. W. Rayner, *Digital Audio Restoration*. London, UK: Springer, 1998.
- [4] L. W. P. Biscainho, P. S. R. Diniz, and P. A. A. Esquef, "ARMA processes in subbands with application to audio restoration." Submitted for publication.