# ARMAX System Identification: First X, then AR, finally MA 

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In this extended abstract, 'process' means: a zero mean, gaussian, stationary, ergodic vector process on $\mathbb{Z}, \perp$ means 'independence', and 'white noise' means a process $\varepsilon$ for which the $\sigma^{t} \varepsilon(0)$ 's are all $\perp$ for $t \in \mathbb{Z}$, and $\sigma$ denotes the shift $(\sigma f(t):=f(t+1))$. Consider the difference equation

$$
W(\sigma) w=E(\sigma) \varepsilon,
$$

(ARMAX)
with $W, E$ suitably sized polynomial matrices. The behavior of (ARMAX) consists of all processes $w$ such that (ARMAX) holds for some white noise process $\varepsilon$. The identification (ID) problem is to obtain estimates of $(W, E)$ from observation of a realization of $w$ :

$$
\tilde{w}(1), \tilde{w}(2), \ldots, \tilde{w}(T) .
$$

In this extended abstract, we will assume for simplicity of exposition that $T=\infty$. In the actual algorithm, we assume $T$ finite, and study the behavior of the estimates as $T \rightarrow \infty$.

Every ARMAX system admits a more refined representation

$$
A(\sigma) R(\sigma) w=M(\sigma) \varepsilon
$$

(AR-MA-X)
with $A$ square, $\operatorname{det}(A)$ non-zero and without unit circle roots, and $R$ left-prime. Note that $R(\sigma) w=0$ corresponds to the 'exogenous' part of the AR-MA-X system (obtained by setting $\varepsilon=0$ ). We call $R$ the ' X ' (exogenous) part, $A$ the 'AR' part,

[^0]and $M$ the 'MA' part of the AR-MA-X system. We present an algorithm that identifies first $R$, then $A$, and finally $M$.

Many interesting problems emerge: When do two systems $(A, R, M)$ define the same behavior? Obtain canonical forms. If $w=\left[\begin{array}{l}u \\ y\end{array}\right]$, when is $u$ a 'free input', in the sense that for any process $u$, there exists a process $y$ such that $w=\left[\begin{array}{l}u \\ y\end{array}\right]$ belongs to the behavior of (AR-MA-X)? When is this $y$ unique? In [1] these issues are studied in depth.

It is easy to see that for all $n \in \mathbb{R}[\xi]$ in the $\mathbb{R}[\xi]$-module generated by the transposes of the rows of $R, n(\sigma)^{\top} w \perp \varepsilon$. Assume that $R=\left[\begin{array}{ll}P & Q\end{array}\right]$ with $P$ square, and correspondingly $w=\left[\begin{array}{l}u \\ y\end{array}\right]$, with $u \perp \varepsilon$. Now look for the finite linear combinations of the rows of the observed

$$
\tilde{W}=\left[\begin{array}{cccccc}
\tilde{w}(1) & \tilde{w}(2) & \tilde{w}(3) & \cdots & \tilde{w}(t) & \cdots \\
\tilde{w}(2) & \tilde{w}(3) & \tilde{w}(4) & \cdots & \tilde{w}(t+1) & \cdots \\
\tilde{w}(3) & \tilde{w}(4) & \tilde{w}(5) & \cdots & \tilde{w}(t+2) & \cdots \\
\vdots & \vdots & \vdots & \vdots & \vdots & \ddots
\end{array}\right]
$$

that are orthogonal to the rows of the observed

$$
\tilde{U}=\left[\begin{array}{cccccc}
\tilde{u}(1) & \tilde{u}(2) & \tilde{u}(3) & \cdots & \tilde{u}(t) & \cdots \\
\tilde{u}(2) & \tilde{u}(3) & \tilde{u}(4) & \cdots & \tilde{u}(t+1) & \cdots \\
\tilde{u}(3) & \tilde{u}(4) & \tilde{u}(5) & \cdots & \tilde{u}(t+2) & \cdots \\
\vdots & \vdots & \vdots & \vdots & \vdots & \ddots
\end{array}\right] .
$$

Call these linear combinations 'orthogonalizers'. Obviously each orthogonalizer is a vector of the form $\pi=\operatorname{col}\left(\pi_{0}, \pi_{1}, \cdots, \pi_{\mathrm{n}}, \cdots\right)$, with the $\pi_{\mathrm{n}}$ 's $\in \mathbb{R}^{\mathrm{w}}$, and all but a finite number of them non-zero. Organize the orthogonalizers as polynomial vectors $\pi(\xi)=\pi_{0}+\pi_{1} \xi+\cdots+\pi_{\mathrm{n}} \xi^{\mathrm{n}}+\cdots \in \mathbb{R}^{\mathrm{W}}[\xi]$.

It can be shown that if $\tilde{u}$ is persistently exciting, then the orthogonalizers form exactly the $\mathbb{R}[\xi]$-module generated by the transposes of the rows of $R$. This yields an algorithm for identifying $R$ from the observations via the orthogonalizers. As we have described it here, this algorithm requires an infinite number of rows of $\tilde{W}$ and $\tilde{U}$, but if we assume that (upper bounds for) the lag $L$ and the dynamic order $n$ of the AR-MA-X system are known, we can restrict attention to the first $L$ rows of $\tilde{W}$ and the first $L+n$ rows of $\tilde{U}$.

Once $R$ has been estimated, we compute

$$
\tilde{a}=\hat{R}(\sigma) \tilde{w},
$$

and obtain an estimate $\hat{A}$ of $A$ from $\tilde{a}$, and proceed by computing

$$
\tilde{m}=\hat{A}(\sigma) \tilde{a},
$$

to obtain an estimate $\hat{M}$ of $M$, leading to an estimate $(\hat{R}, \hat{A}, \hat{M})$ for $(R, A, M)$.
This extended abstract reports on research in progress. A full paper is in preparation.

## References

[1] E.J. Hannan and M. Deistler, The Statistical Theory of Linear Systems, Academic Press, 1979.


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