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Multivariate CARMA processes, continuous-time state space models and complete regularity of the innovations of the sampled processes

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The class of multivariate Lévy-driven autoregressive moving average (MCARMA) processes, the continuous-time analogs of the classical vector ARMA processes, is shown to be equivalent to the class of continuous-time state space models. The linear innovations of the weak ARMA process arising from sampling an MCARMA process at an equidistant grid are proved to be exponentially completely regular (β-mixing) under a mild continuity assumption on the driving Lévy process. It is verified that this continuity assumption is satisfied in most practically relevant situations, including the case where the driving Lévy process has a non-singular Gaussian component, is compound Poisson with an absolutely continuous jump size distribution or has an infinite Lévy measure admitting a density around zero.

Keywords: complete regularity; linear innovations; multivariate CARMA process; sampling; state space representation; strong mixing; vector ARMA process

1. Introduction

CARMA processes are the continuous-time analogs of the widely known discrete-time ARMA processes (see, e.g., [8] for a comprehensive introduction); they were first defined in [12] in the univariate Gaussian setting and have stimulated a considerable amount of research in recent years (see, e.g., [5] and references therein). In particular, the restriction of the driving process to Brownian motion was relaxed and [6] allowed for Lévy processes with finite logarithmic moments. Because of their applicability to irregularly spaced observations and high-frequency data, they have turned out to be a versatile and powerful tool in the modeling of phenomena from the natural sciences, engineering and finance. Recently, [19] extended the concept to multivariate CARMA (MCARMA) processes with the intention of being able to model the joint behavior of several dependent time series. MCARMA processes are thus the continuous-time analogs of discrete-time vector ARMA (VARMA) models (see, e.g., [18]).

The aim of this paper is twofold: first, we establish the equivalence between MCARMA and multivariate continuous-time state space models, a correspondence which is well known in the discrete-time setting [14]; second, we investigate the probabilistic properties of the discrete-time process obtained by recording the values of an MCARMA process at discrete, equally spaced points in time. A detailed understanding of the innovations of the weak VARMA process which arises is a prerequisite for proving asymptotic properties of statistics of a discretely observed MCARMA process. One notion of asymptotic independence which is very useful in this context is complete regularity (see Section 4 for a precise definition) and we show that the innovations of a discretized MCARMA process have this desirable property. Our results therefore not only provide important insight into the probabilistic structure of CARMA processes, but they are also fundamental to the development of an estimation theory for non-Gaussian continuous-time state space models based on equidistant observations.

In this paper, we show that a sampled MCARMA process is a discrete-time VARMA process with dependent innovations. While the mixing behavior of ARMA and more general linear processes is fairly well understood (see, e.g., [1,20,21]), the mixing properties of the innovations of a sampled continuous-time process have received very little attention. From [9], it is only known that the innovations of a discretized univariate Lévy-driven CARMA process are weak white noise, which, by itself, is typically of little help in applications. We show that the linear innovations of a sampled MCARMA process satisfy a set of VARMA equations and we conclude that under a mild continuity assumption on the driving Lévy process, they are geometrically completely regular and, in particular, geometrically strongly mixing. This continuity assumption is further shown to be satisfied for most of the practically relevant choices of the driving Lévy process, including processes with a non-singular Gaussian component, as well as compound Poisson processes with an absolutely continuous jump size distribution and infinite activity processes whose Lévy measures admit a density in a neighborhood of zero.

This paper is structured as follows. In Section 2 we review some well-known properties of Lévy processes, which we will use later. The class of multivariate CARMA processes, in a slightly more general form than in the original definition of [19], is described in detail in Section 3 and shown to be equivalent to the class of continuous-time state space models. In Section 4 the main result about the mixing properties of the sampled processes is stated and demonstrated to be applicable in many practical situations. The proofs of the results are presented in Section 5.

We use the following notation. The space of $m \times n$ matrices with entries in the ring $\mathbb{K}$ is denoted by $M_{m,n}(\mathbb{K})$ or $M_m(\mathbb{K})$ if $m = n$. A^T denotes the transpose of the matrix A, the matrices $\mathbb{I}_m$ and 0_m are the identity and the zero element of $M_m(\mathbb{K})$, respectively, and $A \otimes B$ stands for the Kronecker product of the matrices A and B. The zero vector in $\mathbb{R}^m$ is denoted by $\mathbf{0}_m$, and $\|\cdot\|$ and $\langle\cdot,\cdot\rangle$ represent the Euclidean norm and inner product, respectively. Finally, $\mathbb{K}[z]$ ($\mathbb{K}\{z\}$) is the ring of polynomial (rational) expressions in z over $\mathbb{K}$ and $I_B(\cdot)$ is the indicator function of the set B.

2. Multivariate Lévy processes

In this section we review the definition of a multivariate Lévy process and some elementary facts about these processes which we will use later. More details and proofs can be found in, for instance, [23].

Definition 2.1. *A (one-sided) $\mathbb{R}^m$-valued Lévy process $(\mathbf{L}(t))_{t\geq 0}$ is a stochastic process with stationary, independent increments, continuous in probability and satisfying $\mathbf{L}(0) = \mathbf{0}_m$ almost surely.*

Every $\mathbb{R}^m$-valued Lévy process $(\mathbf{L}(t))_{t\geq 0}$ can be assumed to be càdlàg and is completely characterized by its characteristic function in the Lévy–Khintchine form $\mathbb{E}\mathrm{e}^{\mathrm{i}\langle \mathbf{u},\mathbf{L}(t)\rangle} = \exp\{t\psi^{\mathbf{L}}(\mathbf{u})\}$, $\mathbf{u}\in\mathbb{R}^m$, $t\geq 0$, where $\psi^{\mathbf{L}}$ has the special form

$$\psi^{\mathbf{L}}(\mathbf{u}) = \mathrm{i}\langle \boldsymbol{\gamma}, \mathbf{u}\rangle - \frac{1}{2}\langle \mathbf{u}, \Sigma^{\mathcal{G}}\mathbf{u}\rangle + \int_{\mathbb{R}^m} \bigl[\mathrm{e}^{\mathrm{i}\langle \mathbf{u},\mathbf{x}\rangle} - 1 - \mathrm{i}\langle \mathbf{u}, \mathbf{x}\rangle I_{\{\|x\|\leq 1\}}\bigr]\nu^{\mathbf{L}}(\mathrm{d}\mathbf{x}).$$

The vector $\gamma\in\mathbb{R}^m$ is called the *drift*, the non-negative definite, symmetric $m\times m$ matrix $\Sigma^{\mathcal{G}}$ is the *Gaussian covariance matrix* and $\nu^{\mathbf{L}}$ is a measure on $\mathbb{R}^m$, referred to as the *Lévy measure*, satisfying

$$\nu^{\mathbf{L}}(\{\mathbf{0}_m\}) = 0, \qquad \int_{\mathbb{R}^m} \min(\|\mathbf{x}\|^2, 1)\nu^{\mathbf{L}}(\mathrm{d}\mathbf{x}) < \infty.$$

We will work with two-sided Lévy processes $\mathbf{L} = (\mathbf{L}(t))_{t\in\mathbb{R}}$. These are obtained from two independent copies $(\mathbf{L}_1(t))_{t\geq 0}$, $(\mathbf{L}_2(t))_{t\geq 0}$ of a one-sided Lévy process via the construction

$$\mathbf{L}(t) = \begin{cases} \mathbf{L}_1(t), & t\geq 0, \\ -\lim\limits_{s\nearrow -t} \mathbf{L}_2(s), & t<0. \end{cases}$$

Throughout the paper, we restrict our attention to Lévy processes with zero means and finite second moments.

Assumption L1. *The Lévy process* $\mathbf{L}$ *satisfies* $\mathbb{E}\mathbf{L}(1) = 0$ *and* $\mathbb{E}\|\mathbf{L}(1)\|^2 < \infty$.

The assumption $\mathbb{E}\mathbf{L}(1) = 0$ is made only for notational convenience and is not essential for our results to hold. The premise that $\mathbf{L}$ has finite variance is, in contrast, a true restriction, which is very often made in the analysis of (C)ARMA processes. The treatment of the infinite variance case requires different techniques and often does not lead to comparable results. It is well known that $\mathbf{L}$ has finite second moments if and only if $\int_{\|\mathbf{x}\|\geq 1}\|\mathbf{x}\|^2\nu(\mathrm{d}\mathbf{x})$ is finite, and that $\Sigma^{\mathbf{L}} = \mathbb{E}\mathbf{L}(1)\mathbf{L}(1)^{\mathrm{T}}$ is then given by $\int_{\mathbb{R}^m}\mathbf{x}\mathbf{x}^{\mathrm{T}}\nu^{\mathbf{L}}(\mathrm{d}\mathbf{x}) + \Sigma^{\mathcal{G}}$.

3. MCARMA processes and state space models

If $\mathbf{L}$ is a two-sided Lévy process with values in $\mathbb{R}^m$ and $p>q$ are positive integers, then the d-dimensional $\mathbf{L}$-driven autoregressive moving average (*MCARMA*) process with autoregressive polynomial

$$z\mapsto P(z) := \mathbb{I}_d z^p + A_1 z^{p-1} + \cdots + A_p \in M_d(\mathbb{R}[z]) \tag{3.1a}$$

and moving average polynomial

$$z\mapsto Q(z) := B_0 z^q + B_1 z^{q-1} + \cdots + B_q \in M_{d,m}(\mathbb{R}[z]) \tag{3.1b}$$

is thought of as the solution to the formal differential equation

$$P(D)\mathbf{Y}(t) = Q(D)D\mathbf{L}(t), \qquad D\equiv \frac{\mathrm{d}}{\mathrm{d}t}, \tag{3.2}$$

which is the continuous-time analog of the discrete-time ARMA equations. We note that we allow for the driving Lévy process $\mathbf{L}$ and the $\mathbf{L}$-driven MCARMA process to have different dimensions and thus slightly extend the original definition of [19]. All the results we need from [19] are easily seen to continue to hold in this more general setting. Since, in general, Lévy processes are not differentiable, equation (3.2) is purely formal and, as usual, interpreted as being equivalent to the *state space representation*

$$\mathrm{d}\mathbf{G}(t) = \mathcal{A}\mathbf{G}(t)\,\mathrm{d}t + \mathcal{B}\,\mathrm{d}\mathbf{L}(t), \qquad \mathbf{Y}(t) = \mathcal{C}\mathbf{G}(t), \qquad t \in \mathbb{R}, \tag{3.3}$$

where $\mathcal{A}, \mathcal{B}, \mathcal{C}$ are given by

$$\mathcal{A} = \begin{pmatrix} 0 & \mathbb{I}_d & 0 & \dots & 0 \\ 0 & 0 & \mathbb{I}_d & \ddots & \vdots \\ \vdots & & \ddots & \ddots & 0 \\ 0 & \dots & \dots & 0 & \mathbb{I}_d \\ -A_p & -A_{p-1} & \dots & \dots & -A_1 \end{pmatrix} \in M_{pd}(\mathbb{R}), \tag{3.4a}$$

$$\begin{aligned} &\mathcal{B} = (\beta_1^{\mathrm{T}} \quad \cdots \quad \beta_p^{\mathrm{T}})^{\mathrm{T}} \in M_{pd,m}(\mathbb{R}), \\ &\qquad \beta_{p-j} = -I_{\{0,\dots,q\}}(j)\left[\sum_{i=1}^{p-j-1} A_i\beta_{p-j-i} + B_{q-j}\right] \end{aligned} \tag{3.4b}$$

and

$$\mathcal{C} = (\mathbb{I}_d, 0_d, \dots, 0_d) \in M_{d,pd}(\mathbb{R}). \tag{3.4c}$$

In view of representation (3.3), MCARMA processes are linear continuous-time state space models. We will consider this class of processes and see that it is in fact equivalent to the class of MCARMA models.

Definition 3.1. *An $\mathbb{R}^d$-valued continuous-time linear state space model $(A, B, C, \mathbf{L})$ of dimension N is characterized by an $\mathbb{R}^m$-valued driving Lévy process $\mathbf{L}$, a state transition matrix $A \in M_N(\mathbb{R})$, an input matrix $B \in M_{N,m}(\mathbb{R})$ and an observation matrix $C \in M_{d,N}(\mathbb{R})$. It consists of a state equation of Ornstein–Uhlenbeck type*

$$\mathrm{d}\mathbf{X}(t) = A\mathbf{X}(t)\,\mathrm{d}t + B\,\mathrm{d}\mathbf{L}(t) \tag{3.5a}$$

and an observation equation

$$\mathbf{Y}(t) = C\mathbf{X}(t). \tag{3.5b}$$

The $\mathbb{R}^N$-valued process $\mathbf{X} = (\mathbf{X}(t))_{t\in\mathbb{R}}$ is the state vector process and $\mathbf{Y} = (\mathbf{Y}(t))_{t\in\mathbb{R}}$ is the output process.

A solution $\mathbf{Y}$ to equations (3.5) is called *causal* if for all t, $\mathbf{Y}(t)$ is independent of the σ-algebra generated by $\{\mathbf{L}(s) : s > t\}$. Every solution to equation (3.5a) satisfies

$$\mathbf{X}(t) = \mathrm{e}^{A(t-s)}\mathbf{X}(s) + \int_s^t \mathrm{e}^{A(t-u)} B\,\mathrm{d}\mathbf{L}(u), \qquad s, t \in \mathbb{R},\ s < t. \tag{3.6}$$

The independent increment property of Lévy processes implies that $\mathbf{X}$ is a Markov process. We always work under the following standard causal stationarity assumption.

Assumption E1. *The eigenvalues of A have strictly negative real parts.*

The following is well known [25] and recalls conditions for the existence of a stationary causal solution of the state equation (3.5a) for easy reference.

Proposition 3.2. *If Assumptions L1 and E1 hold, then equation (3.5a) has a unique strictly stationary, causal solution $\mathbf{X}$ given by*

$$\mathbf{X}(t) = \int_{-\infty}^t \mathrm{e}^{A(t-u)} B\,\mathrm{d}\mathbf{L}(u), \qquad t \in \mathbb{R}, \tag{3.7}$$

which has the same distribution as $\int_0^\infty \mathrm{e}^{Au} B\,\mathrm{d}\mathbf{L}(u)$. Moreover, $\mathbf{X}(t)$ has mean zero,

$$\operatorname{Var}(\mathbf{X}(t)) = \mathbb{E}\mathbf{X}(t)\mathbf{X}(t)^{\mathrm{T}} =: \Gamma_0 = \int_0^\infty \mathrm{e}^{Au} B \Sigma^{\mathbf{L}} B^{\mathrm{T}} \mathrm{e}^{A^{\mathrm{T}}u}\,\mathrm{d}u, \tag{3.8a}$$

$$\operatorname{Cov}\big(\mathbf{X}(t+h), \mathbf{X}(t)\big) = \mathbb{E}\mathbf{X}(t+h)\mathbf{X}(t)^{\mathrm{T}} = \mathrm{e}^{Ah}\Gamma_0, \qquad h \geq 0, \tag{3.8b}$$

and Γ_0 satisfies $A\Gamma_0 + \Gamma_0 A^{\mathrm{T}} = -B\Sigma^{\mathbf{L}}B^{\mathrm{T}}$.

It is an immediate consequence that the output process $\mathbf{Y}$ has mean zero and autocovariance function $h \mapsto \gamma_{\mathbf{Y}}(h) = C\mathrm{e}^{Ah}\Gamma_0 C^{\mathrm{T}}$, and that $\mathbf{Y}$ can be written as a moving average of the driving Lévy process as

$$\mathbf{Y}(t) = \int_{-\infty}^{\infty} g(t-u)\,\mathrm{d}\mathbf{L}(u), \qquad t \in \mathbb{R}; \qquad g(t) = C\mathrm{e}^{At} B I_{[0,\infty)}(t). \tag{3.9}$$

These equations serve, with A, B and C defined as in equations (3.4), as the definition of an MCARMA process with autoregressive and moving average polynomials given by equations (3.1). It shows that the behavior of the process $\mathbf{Y}$ depends on the values of the individual matrices A, B, C only through the products $C\mathrm{e}^{At}B$, $t \in \mathbb{R}$. These products are, in turn, intimately related to the rational matrix function $H : z \mapsto C(z\mathbb{I}_N - A)^{-1}B$, which is called the *transfer function* of the state space model (3.5). A pair (P, Q), $P \in M_d(\mathbb{R}[z])$, $Q \in M_{d.m}(\mathbb{R}[z])$, of rational matrix functions is a *left matrix fraction description* for the rational matrix function $H \in M_d(\mathbb{R}\{z\})$ if $P(z)^{-1}Q(z) = H(z)$ for all $z \in \mathbb{C}$. The next theorem gives an answer to the question of what other state space representations besides (3.3) can be used to define an MCARMA process. The proof is given in Section 5.

Theorem 3.3. *If (P, Q) is a left matrix fraction description for the transfer function $z \mapsto C(z\mathbb{I}_N - A)^{-1}B$, then the stationary solution $\mathbf{Y}$ of the state space model $(A, B, C, \mathbf{L})$ defined by equations (3.5) is an $\mathbf{L}$-driven MCARMA process with autoregressive polynomial P and moving average polynomial Q.*

Corollary 3.4. *The classes of MCARMA and causal continuous-time state space models are equivalent.*

Proof. By definition, every MCARMA process is the output process of a state space model. Conversely, given any state space model $(A, B, C, \mathbf{L})$ with output process $\mathbf{Y}$, [10], Appendix 2, Theorem 8, shows that the transfer function $H : z \mapsto C(zI_N - A)^{-1}B$ possesses a left matrix fraction description $H(z) = P(z)^{-1}Q(z)$. Hence, by Theorem 3.3, $\mathbf{Y}$ is an MCARMA process. □

4. Complete regularity of the innovations of a sampled MCARMA process

For a continuous-time stochastic process $\mathbf{Y} = (\mathbf{Y}(t))_{t\in\mathbb{R}}$ and a positive constant h, the corresponding sampled process $\mathbf{Y}^{(h)} = (\mathbf{Y}_n^{(h)})_{n\in\mathbb{Z}}$ is defined by $\mathbf{Y}_n^{(h)} = \mathbf{Y}(nh)$. A common problem in applications is the estimation of a set of model parameters based on observations of the values of a realization of a continuous-time process at equally spaced points in time. In order to make MCARMA processes amenable to parameter inference from equidistantly sampled observations, it is important to have a good understanding of the probabilistic properties of $\mathbf{Y}^{(h)}$. One such property which has turned out to be useful for the derivation of asymptotic properties of estimators is *mixing*, for which there are several different notions (see, e.g., [4] for a detailed exposition). Let I denote $\mathbb{Z}$ or $\mathbb{R}$. For a stationary process $\mathbf{X} = (X_n)_{n\in I}$ on some probability space $(\Omega, \mathscr{F}, \mathbb{P})$, we write $\mathscr{F}_n^m = \sigma(X_j : j \in I, n < j < m)$, $-\infty \leq n < m \leq \infty$. The α-mixing coefficients $(\alpha(m))_{m\in I}$ are then defined by

$$\alpha(m) = \sup_{A\in\mathscr{F}_{-\infty}^0, B\in\mathscr{F}_m^\infty} |\mathbb{P}(A \cap B) - \mathbb{P}(A)\mathbb{P}(B)|.$$

If $\lim_{m\to\infty} \alpha(m) = 0$, then the process $\mathbf{X}$ is called *strongly mixing*, and if there exist constants $C > 0$ and $0 < \lambda < 1$ such that $\alpha_m < C\lambda^m$, $m \geq 1$, it is called *exponentially strongly mixing*. The β-mixing coefficients $(\beta(m))_{m\in I}$ are similarly defined as

$$\beta(m) = \mathbb{E} \sup_{B\in\mathscr{F}_m^\infty} \left|\mathbb{P}(B|\mathscr{F}_{-\infty}^0) - \mathbb{P}(B)\right|.$$

If $\lim_{m\to\infty} \beta(m) = 0$, then the process $\mathbf{X}$ is called *completely regular* or *β-mixing*, and if there exist constants $C > 0$ and $0 < \lambda < 1$ such that $\beta_m < C\lambda^m$, $m \geq 1$, it is called *exponentially completely regular*. It is clear from these definitions that $\alpha(m) \leq \beta(m)$ and that (exponential) complete regularity implies (exponential) strong mixing. It has been shown in [19], Proposition 3.34, that every causal MCARMA process $\mathbf{Y}$ with a finite κth moment, $\kappa > 0$, is strongly mixing and this naturally carries over to the sampled process $\mathbf{Y}^{(h)}$. In this paper, we therefore do not investigate the mixing properties of the process $\mathbf{Y}^{(h)}$ itself, but rather of its linear innovations.

Definition 4.1. *Let $(\mathbf{Y}_n)_{n\in\mathbb{Z}}$ be an $\mathbb{R}^d$-valued stationary stochastic process with finite second moments. The linear innovations $(\boldsymbol{\varepsilon}_n)_{n\in\mathbb{Z}}$ of $(\mathbf{Y}_n)_{n\in\mathbb{Z}}$ are then defined by*

$$\boldsymbol{\varepsilon}_n = \mathbf{Y}_n - P_{n-1}\mathbf{Y}_n, \qquad P_n = \text{orthogonal projection onto } \overline{\operatorname{span}}\{\mathbf{Y}_\nu : -\infty < \nu \le n\}, \tag{4.1}$$

where the closure is taken in the Hilbert space of square-integrable random variables with inner product $(X, Y) \mapsto \mathbb{E}\langle X, Y\rangle$.

From now on, we work under an additional assumption, which is standard in the univariate case.

Assumption E2. *The eigenvalues $\lambda_1, \dots, \lambda_N$ of the state transition matrix A in equation (3.5a) are distinct.*

A polynomial $p \in M_d(\mathbb{C}[z])$ is called *monic* if its leading coefficient is equal to $\mathbb{I}_d$ and *Schur-stable* if the zeros of $z \mapsto \det p(z)$ all lie in the complement of the closed unit disc. We first give a semi-explicit construction of a weak VARMA representation of $\mathbf{Y}^{(h)}$ with complex-valued coefficient matrices, a generalization of [7], Proposition 3.

Theorem 4.2. *Assume that $\mathbf{Y}$ is the output process of the state space system (3.5) satisfying Assumptions L1, E1, E2, and $\mathbf{Y}^{(h)}$ is its sampled version with linear innovations $\boldsymbol{\varepsilon}^{(h)}$. Define the Schur-stable polynomial $\varphi \in \mathbb{C}[z]$ by*

$$\varphi(z) = \prod_{\nu=1}^{N}(1 - \mathrm{e}^{h\lambda_\nu} z) =: (1 - \varphi_1 z - \cdots - \varphi_N z^N). \tag{4.2}$$

There then exists a monic Schur-stable polynomial $\Theta \in M_d(\mathbb{C}[z])$ of degree at most $N-1$ such that

$$\varphi(B)\mathbf{Y}_n^{(h)} = \Theta(B)\boldsymbol{\varepsilon}_n^{(h)}, \qquad n \in \mathbb{Z}, \tag{4.3}$$

where B denotes the backshift operator, that is, $B^j\mathbf{Y}_n^{(h)} = \mathbf{Y}_{n-j}^{(h)}$ for every non-negative integer j.

This result is very important for the proof of the mixing properties of the innovations sequence $\boldsymbol{\varepsilon}^{(h)}$ because it establishes an explicit linear relationship between $\boldsymbol{\varepsilon}^{(h)}$ and $\mathbf{Y}^{(h)}$. A good understanding of the mixing properties of $\boldsymbol{\varepsilon}^{(h)}$ is not only theoretically interesting, but is also practically of considerable relevance for the purpose of statistical inference for multivariate CARMA processes. One estimation procedure in which the importance of the mixing properties of the innovations of the sampled process is clearly visible is Gaussian maximum likelihoood (GML) estimation. Assume that $\Theta \subset \mathbb{R}^s$ is a compact parameter set and that a parametric family of

MCARMA processes is given by the mapping $\Theta \ni \vartheta \mapsto (A_\vartheta, B_\vartheta, C_\vartheta, \mathbf{L}_\vartheta)$. It follows from Theorem 4.2 and [8], Section 11.5, that the Gaussian likelihood of observations $\overline{\mathbf{y}}^L = (\mathbf{y}_1, \dots, \mathbf{y}_L)$ under the model corresponding to a particular value ϑ is given by

$$\mathscr{L}_{\overline{\mathbf{y}}^L}(\vartheta) = (2\pi)^{-Ld/2} \left(\prod_{n=1}^{L} \det V_{\vartheta,n} \right)^{-1/2} \exp\left\{ -\frac{1}{2} \sum_{n=1}^{L} \mathbf{e}_{\vartheta,n}^T V_{\vartheta,n}^{-1} \mathbf{e}_{\vartheta,n} \right\}, \tag{4.4}$$

where $\mathbf{e}_{\vartheta,n}$ is the residual of the minimum mean-squared error linear predictor of $\mathbf{y}_n$ given the preceding observations, and $V_{\vartheta,n}$ is the corresponding covariance matrix. From a practical perspective, it is important to note that all quantities necessary to evaluate the Gaussian likelihood (4.4) can be conveniently computed by using the Kalman recursions ([8], Section 12.2) and the state space representation given in Lemma 5.2. In case the observations $\overline{\mathbf{y}}^L$ are (part of) a realization of the sampled MCARMA process $\mathbf{Y}_{\vartheta_0}^{(h)}$ corresponding to the parameter value ϑ_0, the prediction error sequence $(\mathbf{e}_{\vartheta_0,n})_{n\geq 1}$ is – up to an additive, exponentially decaying term which comes from the initialization of the Kalman filter – (part of) a realization of the innovations sequence $\boldsymbol{\varepsilon}^{(h)}$ of $\mathbf{Y}_{\vartheta_0}^{(h)}$. In order to be able to analyze the asymptotic behavior of the natural GML estimator

$$\hat{\vartheta}^L = \operatorname*{argmax}_{\vartheta \in \Theta} \mathscr{L}_{\overline{\mathbf{y}}^L}(\vartheta)$$

in the limit as $L \to \infty$, it is necessary to have a central limit theorem for sums of the form

$$\frac{1}{\sqrt{L}} \sum_{n=1}^{L} \frac{\partial}{\partial \vartheta} [\log \det V_{\vartheta,n} + \mathbf{e}_{\vartheta,n}^T V_{\vartheta,n}^{-1} \mathbf{e}_{\vartheta,n}] \bigg|_{\vartheta=\vartheta_0}. \tag{4.5}$$

Existing results in the literature [4,15] ensure that various notions of weak dependence, and, in particular, strong mixing, are sufficient for a central limit theorem for the expression (4.5) to hold. Theorem 4.3 below is thus the necessary starting point for the development of an estimation theory for multivariate CARMA processes which involves some additional issues like identifiability of parametrizations and is thus beyond the scope of this paper.

Before presenting the sufficient condition for the innovations $\boldsymbol{\varepsilon}^{(h)}$ to be completely regular, we first observe that the eigenvalues $\lambda_1, \dots, \lambda_N$ of A are the roots of the characteristic polynomial $z \mapsto \det(z\mathbb{I}_N - A)$, which, by the fundamental theorem of algebra, implies that they are either real or occur in complex conjugate pairs. We can therefore assume that they are ordered in such a way that for some $r \in \{0, \dots, N\}$,

$$\lambda_\nu \in \mathbb{R},\ 1 \leq \nu \leq r, \qquad \lambda_\nu = \overline{\lambda_{\nu+1}} \in \mathbb{C}\backslash\mathbb{R}, \qquad \nu = r+1, r+3, \dots, N-1.$$

By Lebesgue's decomposition theorem [16], Theorem 7.33, every measure μ on $\mathbb{R}^d$ can be uniquely decomposed as $\mu = \mu_c + \mu_s$, where μ_c and μ_s are absolutely continuous and singular, respectively, with respect to the d-dimensional Lebesgue measure. If μ_c is not the zero measure, then we say that μ has a non-trivial absolutely continuous component.

Theorem 4.3. *Assume that* $\mathbf{Y}$ *is the output process of the continuous-time state space model* $(A, B, C, \mathbf{L})$ *satisfying Assumptions* L1, E1 *and* E2. *Denote by* $\boldsymbol{\varepsilon}^{(h)}$ *the innovations of the sampled process* $\mathbf{Y}^{(h)}$ *and further assume that the law of the* $\mathbb{R}^{mN}$*-valued random variable*

$$\mathscr{M}^{(h)} = \begin{bmatrix} \mathbf{M}_1^{(h)\mathrm{T}} & \cdots & \mathbf{M}_r^{(h)\mathrm{T}} & \underline{\mathbf{M}}_{r+1}^{(h)\mathrm{T}} & \underline{\mathbf{M}}_{r+3}^{(h)\mathrm{T}} & \cdots & \underline{\mathbf{M}}_{N-1}^{(h)\mathrm{T}} \end{bmatrix}^{\mathrm{T}}, \tag{4.6}$$

where

$$\underline{\mathbf{M}}_\nu^{(h)} = \begin{bmatrix} \operatorname{Re}\mathbf{M}_\nu^{(h)\mathrm{T}} & \operatorname{Im}\mathbf{M}_\nu^{(h)\mathrm{T}} \end{bmatrix}^{\mathrm{T}}, \qquad \mathbf{M}_\nu^{(h)} = \int_0^h \mathrm{e}^{(h-u)\lambda_\nu}\,\mathrm{d}\mathbf{L}(u), \qquad \nu = 1, \ldots, N, \tag{4.7}$$

has a non-trivial absolutely continuous component with respect to the mN*-dimensional Lebesgue measure. Then,* $\boldsymbol{\varepsilon}^{(h)}$ *is exponentially completely regular.*

The assumption on the distribution of $\mathscr{M}^{(h)}$ made in Theorem 4.3 is not very restrictive. Its verification is based on the following lemma, which allows us to derive sufficient conditions in terms of the Lévy process $\mathbf{L}$ which show that it is indeed satisfied in most practical situations.

Lemma 4.4. *There exist matrices* $G \in M_{mN}(\mathbb{R})$ *and* $H \in M_{mN,m}(\mathbb{R})$ *such that* $\mathscr{M}^{(h)} = \mathscr{M}(h)$, *where* $(\mathscr{M}(t))_{t\geq 0}$ *is the unique solution to the stochastic differential equation*

$$\mathrm{d}\mathscr{M}(t) = G\mathscr{M}(t)\,\mathrm{d}t + H\,\mathrm{d}\mathbf{L}(t), \qquad \mathscr{M}(0) = \mathbf{0}_{mN}. \tag{4.8}$$

Moreover, rank $H = m$ *and the* $mN \times mN$ *matrix* $\begin{bmatrix} H & GH & \cdots & G^{N-1}H \end{bmatrix}$ *is non-singular.*

The last part of the statement is referred to as *controllability* of the pair (G, H) and is essential in the proofs of the following explicit sufficient conditions for Theorem 4.3 to hold.

Proposition 4.5. *Assume that the Lévy process* $\mathbf{L}$ *has a non-singular Gaussian covariance matrix* $\Sigma^{\mathcal{G}}$. *Theorem* 4.3 *then holds.*

Proof. By [24], Corollary 2.19, the law of $\mathscr{M}^{(h)}$ is infinitely divisible with Gaussian covariance matrix given by $\int_0^h \mathrm{e}^{Gu} H \Sigma^{\mathcal{G}} H^{\mathrm{T}} \mathrm{e}^{G^{\mathrm{T}}u}\,\mathrm{d}u$. By the controllability of (G, H) and [3], Lemma 12.6.2, this matrix is non-singular and [23], Exercise 29.14 completes the proof. □

A simple Lévy process of practical importance which does not have a non-singular Gaussian covariance matrix is the *compound Poisson Process*, which is defined by $\mathbf{L}(t) = \sum_{n=1}^{N(t)} \mathbf{J}_n$, where $(N(t))_{t\in\mathbb{R}^+}$ is a Poisson process and $(\mathbf{J}_n)_{n\in\mathbb{Z}}$ is an i.i.d. sequence independent of $(N(t))_{t\in\mathbb{R}^+}$; the law of $\mathbf{J}_n$ is called the *jump size distribution*. The proof of [22], Theorem 1.1, in conjunction with Lemma 4.4, implies the following result.

Proposition 4.6. *Assume that* $\mathbf{L}$ *is a compound Poisson process with absolutely continuous jump size distribution. Theorem* 4.3 *then holds.*

Under a similar smoothness assumption, the conclusion of Theorem 4.3 also holds in the case of infinite activity Lévy processes. The statement follows from applying [22], Theorem 1.1, to equation (4.8).

Proposition 4.7. *Assume that the Lévy measure $\nu^{\mathbf{L}}$ of $\mathbf{L}$ satisfies $\nu^{\mathbf{L}}(\mathbb{R}^m) = \infty$ and that there exists a positive constant ρ such that $\nu^{\mathbf{L}}$ restricted to the ball $\{\mathbf{x} \in \mathbb{R}^m : \|\mathbf{x}\| \leq \rho\}$ has a density with respect to the m-dimensional Lebesgue measure. Theorem 4.3 then holds.*

While the preceding three propositions already cover a wide range of Lévy processes encountered in practice, there are some relevant cases which are not yet taken care of, in particular, the construction of the Lévy process as a vector of independent univariate Lévy processes (Corollary 4.11 below). To also cover this and related choices, we employ the polar decomposition for Lévy measures [2], Lemma 2.1. By this result, for every Lévy measure $\nu^{\mathbf{L}}$, there exists a probability measure α on the $(m-1)$-sphere $S^{m-1} := \{\mathbf{x} \in \mathbb{R}^m : \|\mathbf{x}\| = 1\}$ and a family $\{\nu_{\boldsymbol{\xi}} : \boldsymbol{\xi} \in S^{m-1}\}$ of measures on $\mathbb{R}^+$ such that for each Borel set $B \in \mathcal{B}(\mathbb{R}^+)$, the function $\boldsymbol{\xi} \mapsto \nu_{\boldsymbol{\xi}}(B)$ is measurable and

$$\nu^{\mathbf{L}}(B) = \int_{S^{m-1}} \int_0^\infty I_B(\lambda\boldsymbol{\xi}) \nu_{\boldsymbol{\xi}}(\mathrm{d}\lambda)\alpha(\mathrm{d}\boldsymbol{\xi}), \qquad B \in \mathcal{B}(\mathbb{R}^m \backslash \{\mathbf{0}_m\}). \tag{4.9}$$

A hyperplane in a finite-dimensional vector space is a linear subspace of codimension one.

Proposition 4.8. *If the Lévy measure $\nu^{\mathbf{L}}$ has a polar decomposition $(\alpha, \nu_{\boldsymbol{\xi}} : \boldsymbol{\xi} \in S^{m-1})$ such that for any hyperplane $\mathcal{H} \subset \mathbb{R}^m$, it holds that $\int_{S^{m-1}} I_{\mathbb{R}^m\backslash\mathcal{H}}(\boldsymbol{\xi}) \int_0^\infty \nu_{\boldsymbol{\xi}}(\mathrm{d}\lambda)\alpha(\mathrm{d}\boldsymbol{\xi}) = \infty$, then Theorem 4.3 holds.*

Proof. The proof rests on the main theorem of [26]. We denote by $\operatorname{im} H$ the image of the linear operator associated with the matrix H. Since $\operatorname{rank} H = m$ and the pair (G, H) is controllable, we only have to show that $\nu^{\mathbf{L}}(\{\mathbf{x} \in \mathbb{R}^m : H\mathbf{x} \in \operatorname{im} H \backslash \mathcal{H}\}) = \infty$ for all hyperplanes $\mathcal{H} \subset \operatorname{im} H$, and since $\mathbb{R}^m \cong \operatorname{im} H$, the last condition is equivalent to $\nu^{\mathbf{L}}(\mathbb{R}^m \backslash \mathcal{H}) = \infty$ for all hyperplanes $\mathcal{H} \subset \mathbb{R}^m$. Using equation (4.9) and the fact that for every $\boldsymbol{\xi} \in S^{m-1}$ and every $\lambda \in \mathbb{R}^+$, the vector $\lambda\boldsymbol{\xi}$ is in $\mathcal{H}$ if and only if the vector $\boldsymbol{\xi}$ is, this is seen to be equivalent to the assumption of the proposition. □

Corollary 4.9. *If the Lévy measure $\nu^{\mathbf{L}}$ has a polar decomposition $(\alpha, \nu_{\boldsymbol{\xi}} : \boldsymbol{\xi} \in S^{m-1})$ such that $\alpha(S^{m-1} \backslash \mathcal{H})$ is positive for all hyperplanes $\mathcal{H} \in \mathbb{R}^m$ and $\nu_{\boldsymbol{\xi}}(\mathbb{R}^+) = \infty$ for α-almost every $\boldsymbol{\xi}$, then Theorem 4.3 holds.*

Corollary 4.10. *If the Lévy measure $\nu^{\mathbf{L}}$ has a polar decomposition $(\alpha, \nu_{\boldsymbol{\xi}} : \boldsymbol{\xi} \in S^{m-1})$ such that for some linearly independent vectors $\boldsymbol{\xi}_1, \ldots, \boldsymbol{\xi}_m \in S^{m-1}$, it holds that $\alpha(\boldsymbol{\xi}_k) > 0$ and $\nu_{\boldsymbol{\xi}_k}(\mathbb{R}^+) = \infty$ for $k = 1, \ldots, m$, then Theorem 4.3 holds.*

Corollary 4.11. *Assume that $l \geq m$ is an integer and that the matrix $R \in M_{m,l}(\mathbb{R})$ has full rank m. If $\mathbf{L} = R\,(L_1 \ \cdots \ L_l)^{\mathrm{T}}$, where L_k, $k = 1, \ldots, l$, are independent univariate Lévy processes with Lévy measures ν_k^L satisfying $\nu_k^L(\mathbb{R}) = \infty$, then Theorem 4.3 holds.*

5. Proofs

5.1. Proofs for Section 3

Proof of Theorem 3.3. The first step of the proof is to show that any pair (P, Q) of the form (3.1) is a left matrix fraction description of $\mathcal{C}(z\mathbb{I}_{pd} - \mathcal{A})^{-1}\mathcal{B}$, provided $\mathcal{A}$, $\mathcal{B}$ and $\mathcal{C}$ are defined as in equations (3.4). We first show the relation

$$(z\mathbb{I}_{pd} - \mathcal{A})^{-1}\mathcal{B} = [\, w_1(z)^{\mathrm{T}} \quad \cdots \quad w_p^{\mathrm{T}}(z)\,]^{\mathrm{T}}, \tag{5.1}$$

where $w_j(z) \in M_{d,m}(\mathbb{R}\{z\})$, $j = 1, \ldots, p$, are defined by the equations

$$w_j(z) = \frac{1}{z}\big(w_{j+1}(z) + \beta_j\big), \qquad j = 1, \ldots, p-1, \tag{5.2a}$$

and

$$w_p(z) = \frac{1}{z}\left(-\sum_{k=0}^{p-1} A_{p-k} w_{k+1}(z) + \beta_p\right). \tag{5.2b}$$

Since it has been shown in [19], Theorem 3.12, that $w_1(z) = P(z)^{-1}Q(z)$ this will prove the assertion. Equation (5.1) is clearly equivalent to $\mathcal{B} = (z\mathbb{I}_{pd} - \mathcal{A})\left[w_1(z)^{\mathrm{T}} \quad \cdots \quad w_p^{\mathrm{T}}(z)\right]^{\mathrm{T}}$, which explicitly reads

$$\begin{aligned}
\beta_j &= z w_j(z) - w_{j+1}(z), \qquad j = 1, \ldots, p-1, \\
\beta_p &= z w_p(z) + A_p w_1(z) + \cdots + A_1 w_p(z)
\end{aligned}$$

and is thus equivalent to equations (5.2).

For the second step consider a given state space model $(A, B, C, \mathbf{L})$. Using the spectral representation [17], Theorem 17.5,

$$\mathrm{e}^{At} = \frac{1}{2\pi \mathrm{i}} \int_{\Gamma} \mathrm{e}^{zt}(z\mathbb{I}_N - A)^{-1}\,\mathrm{d}z, \qquad t \in \mathbb{R}, \tag{5.3}$$

where Γ is some closed contour in $\mathbb{C}$ winding around each eigenvalue of A exactly once, it follows that

$$\begin{aligned}
\mathbf{Y}(t) &= \int_{-\infty}^{t} C\mathrm{e}^{A(t-u)} B\,\mathrm{d}\mathbf{L}(u) = \frac{1}{2\pi\mathrm{i}} \int_{-\infty}^{t} \int_{\Gamma} \mathrm{e}^{z(t-u)} C(z\mathbb{I}_N - A)^{-1} B\,\mathrm{d}z\,\mathrm{d}\mathbf{L}(u) \\
&= \frac{1}{2\pi\mathrm{i}} \int_{-\infty}^{t} \int_{\Gamma} \mathrm{e}^{z(t-u)} P(z)^{-1} Q(z)\,\mathrm{d}z\,\mathrm{d}\mathbf{L}(u) \\
&= \frac{1}{2\pi\mathrm{i}} \int_{-\infty}^{t} \int_{\Gamma} \mathrm{e}^{z(t-u)} \mathcal{C}(z\mathbb{I}_{pd} - \mathcal{A})^{-1}\mathcal{B}\,\mathrm{d}z\,\mathrm{d}\mathbf{L}(u) \\
&= \int_{-\infty}^{t} \mathcal{C}\mathrm{e}^{\mathcal{A}(t-u)}\mathcal{B}\,\mathrm{d}\mathbf{L}(u),
\end{aligned}$$

where $\mathcal{A}$, $\mathcal{B}$ and $\mathcal{C}$ are defined in terms of (P, Q) by equations (3.4). Thus $\mathbf{Y}$ is an MCARMA process with autoregressive polynomial P and moving average polynomial Q. □

5.2. Proofs for Section 4

In this section we present the proofs of our main results, Theorem 4.2, Theorem 4.3 and Lemma 4.4, as well as several auxiliary results. The first is a generalization of [7], Proposition 2, expressing MCARMA processes as a sum of multivariate Ornstein–Uhlenbeck processes.

Proposition 5.1. *Let* $\mathbf{Y}$ *be the the output process of the state space system* (3.5) *and assume that Assumption* E2 *holds. Then, there exist vectors* $\mathbf{s}_1, \ldots, \mathbf{s}_N \in \mathbb{C}^m \backslash \{\mathbf{0}_m\}$ *and* $\mathbf{b}_1, \ldots, \mathbf{b}_N \in \mathbb{C}^d \backslash \{\mathbf{0}_d\}$ *such that* $\mathbf{Y}$ *can be decomposed into a sum of dependent, complex-valued Ornstein–Uhlenbeck processes as* $\mathbf{Y}(t) = \sum_{\nu=1}^N \mathbf{Y}_\nu(t)$, *where*

$$\mathbf{Y}_\nu(t) = \mathrm{e}^{\lambda_\nu(t-s)}\mathbf{Y}_\nu(s) + \mathbf{b}_\nu \int_s^t \mathrm{e}^{\lambda_\nu(t-u)}\,\mathrm{d}\langle \mathbf{s}_\nu, \mathbf{L}(u)\rangle, \qquad s, t \in \mathbb{R},\ s < t. \tag{5.4}$$

Proof. We first choose a left matrix fraction description (P, Q) of the transfer function $z \mapsto C(z\mathbb{I}_N - A)^{-1}B$ such that $z \mapsto \det P(z)$ and $z \mapsto \det Q(z)$ have no common zeros and $z \mapsto \det P(z)$ has no multiple zeros. This is always possible, by Assumption E2. Inserting the spectral representation (5.3) of e^{At} into the kernel $g(t)$ (equation (3.9)), we get $g(t) = \frac{1}{2\pi \mathrm{i}}\int_\Gamma \mathrm{e}^{zt} C(z\mathbb{I}_N - A)^{-1}B\,\mathrm{d}z I_{[0,\infty)}(t)$ and, by construction, the integrand equals $\mathrm{e}^{zt}P(z)^{-1}Q(z)I_{[0,\infty)}(t)$. After writing $P(z)^{-1} = \frac{1}{\det P(z)}\operatorname{adj} P(z)$, where adj denotes the adjugate of a matrix, an elementwise application of the residue theorem from complex analysis ([11], Theorem 9.16.1) shows that

$$g(t) = \sum_{\nu=1}^N \mathrm{e}^{\lambda_\nu t}\frac{1}{(\det P)'(\lambda_\nu)}\operatorname{adj} P(\lambda_\nu)Q(\lambda_\nu)I_{[0,\infty)}(t),$$

where $(\det P)'(\lambda_\nu) := \frac{\mathrm{d}}{\mathrm{d}z}\det P(z)|_{z=\lambda_\nu}$ is non-zero because $z \mapsto \det P(z)$ has only simple zeros. The same fact, in conjunction with the Smith decomposition of P ([3], Theorem 4.7.5), also implies that $\operatorname{rank} P(\lambda_\nu) = d - 1$ and thus $\operatorname{rank}\operatorname{adj} P(\lambda_\nu) = 1$ ([3], Fact 2.14.7(ii)). Since $\det P$ and $\det Q$ have no common zeros, $[(\det P)'(\lambda_\nu)]^{-1}\operatorname{adj} P(\lambda_\nu)Q(\lambda_\nu)$ also has rank one and can thus be written as $\mathbf{b}_\nu\mathbf{s}_\nu^{\mathrm{T}}$ for some non-zero $\mathbf{s}_\nu \in \mathbb{C}^m$ and $\mathbf{b}_\nu \in \mathbb{C}^d$ ([13], Section 51, Theorem 1). □

Lemma 5.2. *Assume that* $\mathbf{Y}$ *is the output process of the state space model* (3.5). *The sampled process* $\mathbf{Y}^{(h)}$ *then has the state space representation*

$$\mathbf{X}_n = \mathrm{e}^{Ah}\mathbf{X}_{n-1} + \mathbf{N}_n, \qquad \mathbf{N}_n = \int_{(n-1)h}^{nh} \mathrm{e}^{A(nh-u)}B\,\mathrm{d}\mathbf{L}_u, \qquad \mathbf{Y}_n^{(h)} = C\mathbf{X}_n^{(h)}. \tag{5.5}$$

The sequence $(\mathbf{N}_n)_{n\in\mathbb{Z}}$ *is i.i.d. with mean zero and covariance matrix*

$$\Sigma\!\!\!/ = \mathbb{E}\mathbf{N}_n\mathbf{N}_n^T = \int_0^h \mathrm{e}^{Au} B\Sigma^{\mathbf{L}} B^T \mathrm{e}^{A^T u}\, \mathrm{d}u. \tag{5.6}$$

Proof. Equations (5.5) follow from setting $t = nh$, $s = (n-1)h$ in equation (3.6). It is an immediate consequence of the Lévy process $\mathbf{L}$ having independent, homogeneous increments that the sequence $(\mathbf{N}_n)_{n\in\mathbb{Z}}$ is i.i.d. and that its covariance matrix $\Sigma\!\!\!/$ is given by equation (5.6). □

From this, we can now proceed to prove the weak vector ARMA representation of the process $\mathbf{Y}^{(h)}$.

Proof of Theorem 4.2. It follows from setting $t = nh$, $s = (n-1)h$ in equation (5.4) that $\mathbf{Y}_n^{(h)}$ can be decomposed as $\mathbf{Y}_n^{(h)} = \sum_{\nu=1}^N \mathbf{Y}_{\nu,n}^{(h)}$, where $\mathbf{Y}_\nu^{(h)}$, satisfying

$$\mathbf{Y}_{\nu,n}^{(h)} = \mathrm{e}^{\lambda_\nu h}\mathbf{Y}_{\nu,n-1}^{(h)} + \mathbf{Z}_{\nu,n}^{(h)}, \qquad \mathbf{Z}_{\nu,n}^{(h)} = \mathbf{b}_\nu \int_{(n-1)h}^{nh} \mathrm{e}^{\lambda_\nu(nh-u)}\, \mathrm{d}\langle \mathbf{s}_\nu, \mathbf{L}(u)\rangle,$$

are the sampled versions of the component MCAR(1) processes from Proposition 5.1. Analogously to [9], Lemma 2.1, we can show by induction that for each $k \in \mathbb{N}_0$ and all complex $d\times d$ matrices $c_1,\ldots,c_k$, it holds that

$$\begin{aligned}\mathbf{Y}_{\nu,n}^{(h)} &= \sum_{r=1}^k c_r \mathbf{Y}_{\nu,n-r}^{(h)} + \left[\mathrm{e}^{\lambda_\nu hk} - \sum_{r=1}^k c_r \mathrm{e}^{\lambda_\nu h(k-r)}\right]\mathbf{Y}_{\nu,n-k}^{(h)} \\ &\quad + \sum_{r=0}^{k-1}\left[\mathrm{e}^{\lambda_\nu hr} - \sum_{j=1}^r c_j \mathrm{e}^{\lambda_\nu h(r-j)}\right]\mathbf{Z}_{\nu,n-r}^{(h)}.\end{aligned} \tag{5.7}$$

If we then use the fact that $\mathrm{e}^{-h\lambda_\nu}$ is a root of $z \mapsto \varphi(z)$, which means that $\mathrm{e}^{Nh\lambda_\nu} - \varphi_1 \mathrm{e}^{(N-1)h\lambda_n u} - \cdots - \varphi_N = 0$, and set $k = N$, $c_r = \mathbb{I}_d\varphi_r$, then equation (5.7) becomes

$$\varphi(B)\mathbf{Y}_{\nu,n}^{(h)} = \sum_{r=0}^{N-1}\left[\mathrm{e}^{rh\lambda_\nu} - \sum_{j=1}^r \varphi_j \mathrm{e}^{\lambda_\nu h(r-j)}\right]\mathbf{Z}_{\nu,n-r}^{(h)}.$$

Summing over ν and rearranging shows that this can be written as

$$\varphi(B)\mathbf{Y}_n^{(h)} = \sum_{\nu=1}^N \mathbf{V}_{\nu,n-\nu+1}^{(h)}, \tag{5.8}$$

where the i.i.d. sequences $(\mathbf{V}_{\nu,n}^{(h)})_{n\in\mathbb{Z}}$, $\nu \in \{1,\ldots,N\}$, are defined by

$$\mathbf{V}_{\nu,n}^{(h)} = \int_{(n-1)h}^{nh} \sum_{\mu=1}^N \mathbf{b}_\mu \left[\mathrm{e}^{\lambda_\mu h(\nu-1)} - \sum_{\kappa=1}^{\nu-1}\varphi_\kappa \mathrm{e}^{\lambda_\mu h(\nu-\kappa-1)}\right]\mathrm{e}^{\lambda_\mu(nh-u)}\, \mathrm{d}\langle \mathbf{s}_\mu, \mathbf{L}(u)\rangle. \tag{5.9}$$

By a straightforward generalization of [8], Proposition 3.2.1, there exists a monic Schur-stable polynomial $\Theta(z) = \mathrm{I}_d + \Theta_1 z + \cdots + \Theta_{N-1} z^{N-1}$ and a white noise sequence $\tilde{\boldsymbol{\varepsilon}}$ such that the $(N-1)$-dependent sequence $\varphi(B)\mathbf{Y}^{(h)}$ has the moving average representation $\varphi(B)\mathbf{Y}_n^{(h)} = \Theta(B)\tilde{\boldsymbol{\varepsilon}}_n$. Since both φ and Θ are monic, and φ is Schur stable (by Assumption E1), $\tilde{\boldsymbol{\varepsilon}}$ is the innovation process of $\mathbf{Y}^{(h)}$ and so it follows that $\tilde{\boldsymbol{\varepsilon}} = \boldsymbol{\varepsilon}^{(h)}$ because the innovations of a stochastic process are uniquely determined. □

As a corollary, we obtain that the innovations sequence $\boldsymbol{\varepsilon}^{(h)}$ itself satisfies a set of strong VARMA equations, the attribute *strong* referring to the fact that the noise sequence is i.i.d., not merely white noise.

Corollary 5.3. *Assume that* $\mathbf{Y}$ *is the output process of the state space system* (3.5) *satisfying Assumptions* L1, E1 *and* E2. *Further assume that* $\boldsymbol{\varepsilon}^{(h)}$ *is the innovations sequence of the sampled process* $\mathbf{Y}^{(h)}$. *There then exists a monic, Schur-stable polynomial* $\Theta \in M_d(\mathbb{C}[z])$ *of degree at most* $N-1$, *a polynomial* $\theta \in M_{d,dN}(\mathbb{R}[z])$ *of degree* $N-1$ *and a* C^{dN}*-valued i.i.d. sequence* $\mathbf{W}^{(h)} = (\mathbf{W}_n^{(h)})_{n\in\mathbb{Z}}$, *such that*

$$\Theta(B)\boldsymbol{\varepsilon}_n^{(h)} = \theta(B)\mathbf{W}_n^{(h)}, \qquad n \in \mathbb{Z}. \tag{5.10}$$

Proof. Combining equations (4.3) and (5.8) gives

$$\begin{aligned} &\boldsymbol{\varepsilon}_n^{(h)} + \Theta_1^{(h)}\boldsymbol{\varepsilon}_{n-1} + \cdots + \Theta_{N-1}^{(h)}\boldsymbol{\varepsilon}_{n-N+1} \\ &\quad = \mathbf{V}_{1,n}^{(h)} + \mathbf{V}_{2,n-1}^{(h)} + \cdots + \mathbf{V}_{N,n-N+1}^{(h)}, \qquad n \in \mathbb{Z}, \end{aligned} \tag{5.11}$$

and with the definitions

$$\mathbf{W}_n^{(h)} = \begin{bmatrix} \mathbf{V}_{1,n}^{(h)\,\mathrm{T}} & \cdots & \mathbf{V}_{N,n}^{(h)\,\mathrm{T}} \end{bmatrix}^{\mathrm{T}} \in \mathbb{C}^{dN}, \qquad n \in \mathbb{Z}, \tag{5.12a}$$

$$\begin{aligned} &\theta(z) = \sum_{j=1}^{N} \theta_j z^{j-1}, \\ &\theta_\nu = [\underbrace{0_d \ \cdots \ 0_d}_{\nu-1 \text{ times}} \ \ \mathbb{I}_d \ \ \underbrace{0_d \ \cdots \ 0_d}_{N-\nu \text{ times}}] \in M_{d,dN}(\mathbb{R}), \qquad \nu = 1,\ldots,N, \end{aligned} \tag{5.12b}$$

equation (5.11) becomes $\Theta(B)\boldsymbol{\varepsilon}_n^{(h)} = \theta(B)\mathbf{W}_n^{(h)}$, showing that $\boldsymbol{\varepsilon}^{(h)}$ is indeed a vector ARMA process. □

This corollary is the central step in establishing complete regularity of the innovations process $\boldsymbol{\varepsilon}^{(h)}$.

Proof of Theorem 4.3. We define the $\mathbb{R}^{mN}$-valued random variables

$$\mathscr{M}_n^{(h)} = \begin{bmatrix} \mathbf{M}_{n,1}^{(h)\,\mathrm{T}} & \cdots & \mathbf{M}_{n,r}^{(h)\,\mathrm{T}} & \underline{\mathbf{M}}_{n,r+1}^{(h)\,\mathrm{T}} & \underline{\mathbf{M}}_{n,r+3}^{(h)\,\mathrm{T}} & \cdots & \underline{\mathbf{M}}_{n,N-1}^{(h)\,\mathrm{T}} \end{bmatrix}^{\mathrm{T}}, \qquad n \in \mathbb{Z},$$

where

$$\underline{\mathbf{M}}_{n,\nu}^{(h)} = \left[\operatorname{Re}\mathbf{M}_{n,\nu}^{(h)\,\mathrm{T}} \quad \operatorname{Im}\mathbf{M}_{n,\nu}^{(h)\,\mathrm{T}}\right]^{\mathrm{T}},$$

$$\mathbf{M}_{n,\nu}^{(h)} = \int_{(n-1)h}^{nh} \mathrm{e}^{\lambda_\nu(nh-u)}\,\mathrm{d}\mathbf{L}(u), \qquad \nu = 1,\ldots,N,\ n\in\mathbb{Z}.$$

Clearly, the sequence $(\mathscr{M}_n^{(h)})_{n\in\mathbb{Z}}$ is i.i.d. and $\mathscr{M}^{(h)}$ is equal to $\mathscr{M}_1^{(h)}$. We now argue that the vector $\mathbf{W}_n^{(h)}$, as defined in equation (5.12a), is equal to a linear transformation of $\mathscr{M}_n^{(h)}$. By equation (5.9), $\mathbf{W}_n^{(h)} = [\Gamma^{\mathrm{T}}\otimes\mathbb{I}_d]\left[(\mathbf{b}_1\mathbf{s}_1^{\mathrm{T}}\mathbf{M}_{n,1}^{(h)})^{\mathrm{T}} \ \cdots \ (\mathbf{b}_N\mathbf{s}_N^{\mathrm{T}}\mathbf{M}_{n,N}^{(h)})^{\mathrm{T}}\right]^{\mathrm{T}}$, where $\Gamma = (\gamma_{\mu,\nu}) \in M_N(\mathbb{C})$ is given by $\gamma_{\mu,\nu} = \mathrm{e}^{\lambda_\mu h(\nu-1)} + \sum_{\kappa=1}^{\nu-1}\varphi_\kappa \mathrm{e}^{\lambda_\mu h(\nu-\kappa-1)}$. With the notation

$$B = \begin{pmatrix} \mathbf{b}_1 & \mathbf{0}_d & \ldots & \mathbf{0}_d \\ \mathbf{0}_d & \mathbf{b}_2 & \ddots & \vdots \\ \vdots & \ddots & \ddots & \mathbf{0}_d \\ \mathbf{0}_d & \ldots & \mathbf{0}_d & \mathbf{b}_N \end{pmatrix} \in M_{dN,N}(\mathbb{C}), \qquad S = \begin{pmatrix} \mathbf{s}_1^{\mathrm{T}} & \mathbf{0}_d^{\mathrm{T}} & \ldots & \mathbf{0}_d^{\mathrm{T}} \\ \mathbf{0}_d^{\mathrm{T}} & \mathbf{s}_2^{\mathrm{T}} & \ddots & \vdots \\ \vdots & \ddots & \ddots & \mathbf{0}_d^{\mathrm{T}} \\ \mathbf{0}_d^{\mathrm{T}} & \ldots & \mathbf{0}_d^{\mathrm{T}} & \mathbf{s}_N^{\mathrm{T}} \end{pmatrix} \in M_{N,mN}(\mathbb{C}),$$

we get $\left[(\mathbf{b}_1\mathbf{s}_1^{\mathrm{T}}\mathbf{M}_{n,1}^{(h)})^{\mathrm{T}} \ \cdots \ (\mathbf{b}_N\mathbf{s}_N^{\mathrm{T}}\mathbf{M}_{n,N}^{(h)})^{\mathrm{T}}\right]^{\mathrm{T}} = BS\left[\mathbf{M}_{n,1}^{(h)\,\mathrm{T}} \ \cdots \ \mathbf{M}_{n,N}^{(h)\,\mathrm{T}}\right]^{\mathrm{T}}$. We recall that for $\nu = r+1, r+3, \ldots, N-1$, the eigenvalues of A satisfy $\lambda_\nu = \overline{\lambda_{\nu+1}} \in \mathbb{C}\backslash\mathbb{R}$, which implies that

$$\mathbf{M}_{n,\nu}^{(h)} = \operatorname{Re}\mathbf{M}_{n,\nu}^{(h)} + \mathrm{i}\operatorname{Im}\mathbf{M}_{n,\nu}^{(h)} \quad \text{and} \quad \mathbf{M}_{n,\nu+1}^{(h)} = \overline{\mathbf{M}_{n,\nu}^{(h)}} = \operatorname{Re}\mathbf{M}_{n,\nu}^{(h)} - \mathrm{i}\operatorname{Im}\mathbf{M}_{n,\nu}^{(h)}.$$

Consequently, we obtain that $\left[\mathbf{M}_{n,1}^{(h)\,\mathrm{T}} \ \cdots \ \mathbf{M}_{n,N}^{(h)\,\mathrm{T}}\right]^{\mathrm{T}} = [K\otimes\mathbb{I}_m]\mathscr{M}_n^{(h)}$, where

$$K = \begin{pmatrix} \mathbb{I}_r & & & \\ & J & & \\ & & \ddots & \\ & & & J \end{pmatrix} \in M_N(\mathbb{C}), \qquad J = \begin{pmatrix} 1 & \mathrm{i} \\ 1 & -\mathrm{i} \end{pmatrix},$$

so that, in total, $\mathbf{W}_n^{(h)} = F\mathscr{M}_n^{(h)}$ with $F = [\Gamma^{\mathrm{T}}\otimes\mathbb{I}_d]BS[K\otimes\mathbb{I}_m] \in M_{dN,mN}(\mathbb{C})$. It follows that the VARMA equation (5.10) for $\boldsymbol{\varepsilon}^{(h)}$ becomes $\Theta(B)\boldsymbol{\varepsilon}_n^{(h)} = \tilde{\theta}(B)\mathscr{M}_n^{(h)}$, where $\tilde{\theta}(z) = \theta(z)F$. By the invertibility of Θ, the transfer function $k: z\mapsto \Theta(z)^{-1}\tilde{\theta}(z)$ is analytic in a disc containing the unit disc and permits a power series expansion $k(z) = \sum_{j=0}^{\infty}\Psi_j z^j$. We next argue that the impulse responses Ψ_j are necessarily *real* $d\times mN$ matrices. Since both $\boldsymbol{\varepsilon}_n^{(h)}$ and $\mathscr{M}_n^{(h)}$ are real-valued, it follows from taking the imaginary part of the equation $\boldsymbol{\varepsilon}_n^{(h)} = k(B)\mathscr{M}_n^{(h)}$ that $\mathbf{0}_d = \sum_{j=0}^{\infty}\operatorname{Im}\Psi_j\mathscr{M}_{n-j}^{(h)}$. Consequently, $0 = \operatorname{Cov}(\mathbf{0}_d) = \sum_{j=0}^{\infty}\operatorname{Im}\Psi_j\operatorname{Cov}(\mathscr{M}_{n-j}^{(h)})\operatorname{Im}\Psi_j^{\mathrm{T}}$ and since each term in the sum is a positive semidefinite matrix, it follows that $\operatorname{Im}\Psi_j\operatorname{Cov}(\mathscr{M}_{n-j}^{(h)})\operatorname{Im}\Psi_j^{\mathrm{T}} = 0$ for every j. The existence of an absolutely continuous component of the law of $\mathscr{M}_{n-j}^{(h)}$ with respect to the mN-dimensional Lebesgue measure implies that $\operatorname{Cov}(\mathscr{M}_{n-j}^{(h)})$ is non-singular and it thus follows that $\operatorname{Im}\Psi_j = 0$ for every j. Hence, $k(z) \in M_{d,mN}(\mathbb{R})$ for all real z, and consequently $k \in M_{d,mN}(\mathbb{R}\{z\})$. [14], Theorem 1.2.1(iii), then implies that there exists a stable $(\mathscr{M}_n^{(h)})_{n\in\mathbb{N}}$-driven VARMA model for $\boldsymbol{\varepsilon}^{(h)}$ with real-valued coefficient matrices. It has been shown in [20], Theorem 1, that a stable vector ARMA process is geometrically completely regular provided that the driving noise sequence is i.i.d. and absolutely continuous with respect to the Lebesgue measure. A careful analysis of the proof of this result shows that the existence of an absolutely continuous component of the law of the driving noise is already sufficient for the conclusion to hold. We briefly comment on the necessary modifications to the argument. We first note that under these weaker assumptions, the proof of [20], Lemma 3, implies that the n-step transition probabilities $P^n(\mathbf{x},\cdot)$ of the Markov chain X associated with a vector ARMA model via its state space representation have an absolutely continuous component for all n greater than or equal to some n_0. This immediately implies aperiodicity and ϕ-irreducibility of X, where ϕ can be taken as the Lebesgue measure restricted to the support of the continuous component of $P^{n_0}(\mathbf{x},\cdot)$. The rest of the proof, in particular the verification of the Foster–Lyapunov drift condition for complete regularity, is unaltered. This shows that $\boldsymbol{\varepsilon}^{(h)}$ is geometrically completely regular and, in particular, strongly mixing with exponentially decaying mixing coefficients. □

Proof of Lemma 4.4. By definition, $\mathbf{M}_\nu^{(h)} = \mathbf{M}_\nu(h)$, where $(\mathbf{M}_\nu(t))_{t\geq 0}$ is the solution to

$$\mathrm{d}\mathbf{M}_\nu(t) = \lambda_\nu \mathbf{M}_\nu(t)\,\mathrm{d}t + \mathrm{d}\mathbf{L}(t), \qquad \mathbf{M}_\nu(0) = \mathbf{0}_m.$$

Taking the real and imaginary parts of this equation gives

$$\begin{aligned}\mathrm{d}\operatorname{Re}\mathbf{M}_\nu(t) &= \operatorname{Re}\lambda_\nu\mathbf{M}_\nu(t)\,\mathrm{d}t + \mathrm{d}\mathbf{L}(t) = [\operatorname{Re}\lambda_\nu\operatorname{Re}\mathbf{M}_\nu(t) - \operatorname{Im}\lambda_\nu\operatorname{Im}\mathbf{M}_\nu(t)]\,\mathrm{d}t + \mathrm{d}\mathbf{L}(t),\\ \mathrm{d}\operatorname{Im}\mathbf{M}_\nu(t) &= \operatorname{Im}\lambda_\nu\mathbf{M}_\nu(t)\,\mathrm{d}t = [\operatorname{Re}\lambda_\nu\operatorname{Im}\mathbf{M}_\nu(t) + \operatorname{Im}\lambda_\nu\operatorname{Re}\mathbf{M}_\nu(t)]\,\mathrm{d}t,\end{aligned}$$

and consequently

$$\mathrm{d}\begin{pmatrix}\operatorname{Re}\mathbf{M}_\nu(t)\\ \operatorname{Im}\mathbf{M}_\nu(t)\end{pmatrix} = [\Lambda_\nu\otimes\mathbb{I}_m]\begin{pmatrix}\operatorname{Re}\mathbf{M}_\nu(t)\\ \operatorname{Im}\mathbf{M}_\nu(t)\end{pmatrix}\mathrm{d}t + \begin{pmatrix}\mathbb{I}_m\\ 0_m\end{pmatrix}\mathrm{d}\mathbf{L}(t), \qquad \Lambda_\nu = \begin{pmatrix}\operatorname{Re}\lambda_\nu & -\operatorname{Im}\lambda_\nu\\ \operatorname{Im}\lambda_\nu & \operatorname{Re}\lambda_\nu\end{pmatrix}.$$

Using the fact that $\lambda_\nu \in \mathbb{R}$ for $\nu = 1,\ldots,r$ and $\lambda_\nu = \overline{\lambda_{\nu+1}} \in \mathbb{C}\backslash\mathbb{R}$ for $\nu = r+1, r+3,\ldots,N-1$, it follows that $\mathscr{M}^{(h)} = \mathscr{M}(h)$, where $(\mathscr{M}(t))_{t\geq 0}$ satisfies $\mathrm{d}\mathscr{M}(t) = G\mathscr{M}(t)\,\mathrm{d}t + H\,\mathrm{d}\mathbf{L}(t)$, and $G = \tilde{G}\otimes\mathbb{I}_m \in M_{mN}(\mathbb{R})$ and $H = \tilde{H}\otimes\mathbb{I}_m \in M_{mN,m}$ are given by

$$\begin{aligned}\tilde{G} &= \operatorname{diag}(\lambda_1,\ldots,\lambda_r,\Lambda_{r+1},\Lambda_{r+3},\ldots,\Lambda_{N-1}),\\ \tilde{H} &= (\underbrace{1 \;\; \cdots \;\; 1}_{r\text{ times}} \;\; 1 \;\; 0 \;\; 1 \;\; 0 \;\; \cdots \;\; 1 \;\; 0)^{\mathrm{T}}.\end{aligned}$$

Since $\operatorname{rank} H = m$, the first claim of the lemma is proved. Next, we show that the controllability matrix $\mathscr{C} := \begin{bmatrix}H & GH & \cdots & G^{N-1}H\end{bmatrix} \in M_{mN}(\mathbb{R})$ is non-singular. With $\widetilde{\mathscr{C}} := \begin{bmatrix}\tilde{H} & \tilde{G}\tilde{H} & \cdots & \tilde{G}^{N-1}\tilde{H}\end{bmatrix}$ and by the properties of the Kronecker product, it follows that $\mathscr{C} = \widetilde{\mathscr{C}}\otimes\mathbb{I}_m$ and thus

$\det \mathscr{C} = [\det \widetilde{\mathscr{C}}]^m$. The matrix $\widetilde{\mathscr{C}}$ is given explicitly by

$$\widetilde{\mathscr{C}} = \begin{pmatrix} 1 & \lambda_1 & \lambda_1^2 & \cdots & \lambda_1^{N-1} \\ \vdots & & & & \vdots \\ 1 & \lambda_r & \lambda_r^2 & \cdots & \lambda_r^{N-1} \\ 1 & \operatorname{Re}\lambda_{r+1} & \operatorname{Re}\lambda_{r+1}^2 & \cdots & \operatorname{Re}\lambda_{r+1}^{N-1} \\ 0 & \operatorname{Im}\lambda_{r+1} & \operatorname{Im}\lambda_{r+1}^2 & \cdots & \operatorname{Im}\lambda_{r+1}^{N-1} \\ \vdots & & & & \vdots \\ 1 & \operatorname{Re}\lambda_{N-1} & \operatorname{Re}\lambda_{N-1}^2 & \cdots & \operatorname{Re}\lambda_{N-1}^{N-1} \\ 0 & \operatorname{Im}\lambda_{N-1} & \operatorname{Im}\lambda_{N-1}^2 & \cdots & \operatorname{Im}\lambda_{N-1}^{N-1} \end{pmatrix} = T \begin{pmatrix} 1 & \lambda_1 & \lambda_1^2 & \cdots & \lambda_1^{N-1} \\ \vdots & & & & \vdots \\ 1 & \lambda_r & \lambda_r^2 & \cdots & \lambda_r^{N-1} \\ 1 & \lambda_{r+1} & \lambda_{r+1}^2 & \cdots & \lambda_{r+1}^{N-1} \\ \mathrm{i} & \mathrm{i}\overline{\lambda_{r+1}} & \mathrm{i}\overline{\lambda_{r+1}^2} & \cdots & \mathrm{i}\overline{\lambda_{r+1}^{N-1}} \\ \vdots & & & & \vdots \\ 1 & \lambda_{N-1} & \lambda_{N-1}^2 & \cdots & \lambda_{N-1}^{N-1} \\ \mathrm{i} & \mathrm{i}\overline{\lambda_{N-1}} & \mathrm{i}\overline{\lambda_{N-1}^2} & \cdots & \mathrm{i}\overline{\lambda_{N-1}^{N-1}} \end{pmatrix}$$

with $T \in M_N(\mathbb{R})$ given by $T = \operatorname{diag}(1, \ldots, 1, R, \ldots, R)$, $R = \frac{1}{2}\begin{pmatrix} 1 & -\mathrm{i} \\ -\mathrm{i} & 1 \end{pmatrix}$. Hence, the formula for the determinant of a Vandermonde matrix ([3], Fact 5.13.3) implies that

$$\det \mathscr{C} = \Bigg[(-1)^{(N-r)/2} \prod_{1 \le \mu < \nu \le r} (\lambda_\mu - \lambda_\nu) \prod_{\substack{\mu,\nu \in I_{r,N} \\ \mu < \nu}} \operatorname{Im}\lambda_\mu |\lambda_\mu - \lambda_\nu|^2 \times |\overline{\lambda_\mu} - \lambda_\nu|^2 \prod_{\substack{1 \le \mu \le r \\ \nu \in I_{r,N}}} |\lambda_\mu - \lambda_\nu|^2 \Bigg]^m,$$

where $I_{r,N} = \{r+1, r+3, \ldots, N-1\}$. Hence, $\det \mathscr{C}$ is not zero by Assumption E2 and the proof is complete. □

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