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Impulse response estimation of massive multi-input systems

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ABSTRACT

Impulse response estimation of massive multi-input systems requires the development of new approaches due to constraints imposed by conventional methods. Two key challenges which need to be addressed are, firstly, the requirement on the perturbation signal period and secondly, the processing time. A novel identification technique is proposed using a set of correlated signals with an iterative algorithm to overcome these challenges. In particular, it is shown that for a system with 100 inputs, the proposed technique is capable of reducing the minimum signal period by a factor of 2.4 compared with a current state-of-the-art algorithm. Additionally, the low computational complexity allows the proposed technique to be utilised for massive systems with long impulse responses.

1. Introduction

The identification of impulse responses is very important in a wide range of applications. One of the most popular models used in the industry for incorporation into model predictive controllers is based on truncated impulse responses (Camacho & Bordons, 2007). In Cespedes and Sun (2014), impulse response analysis was utilised for online grid impedance measurements, in the application of adaptive control of grid-connected inverters. In the area of communications, truncated impulse responses are often used to model communication channels such as multipath channels (Chien, 2015). In the rapidly growing area of electric and hybrid electric vehicles, determination of the impulse response of lithium-ion battery leads to more accurate estimation of its real-time state-of-charge compared with methods relying on the open circuit voltage of the battery and current integration during charge and discharge (Ranjbar, Banaei, Khoobroo, & Fahimi, 2012).

Techniques for impulse response estimation in the single-input case include direct measurement of output subject to impulse input (Visacro, Guimarães, & Araujo, 2013), differentiating the step response (Goora, Colpitts, & Balcom, 2014), convolution of the output with an inverse filter (Novák, Simon, Kadlec, & Lotton, 2010) and correlation methods (Marconato, Ljung, Rolain, & Schoukens, 2014). In the multi-input scenario, three significantly different approaches are available using simultaneous perturbation, in the absence of smoothness assumptions. Simultaneous perturbation holds an important advantage over sequential perturbation as it ensures that the identification is carried out for all the input-output channels under the same conditions. The use of periodic excitations is beneficial in avoiding the effects of leakage and allowing the exploitation of harmonic suppression.

The first simultaneous perturbation approach solves for the frequency response function by measuring output data collected from a series of experiments using multisine excitations (Dobrowiecki, Schoukens, & Guillaume, 2006). It has the advantages of simple signal design and straightforward signal processing of the measured output signals. However, this option is feasible only if multiple experiments can be accommodated. The second approach exploits sets of signals which are uncorrelated with one another to decouple the effects of the individual inputs on the system output (Jin, Wang, Wang, & Yang, 2013; Roinila, Huusari, & Vilkko, 2013; Roinila, Messo, & Santi, 2017; Tan, Barker, & Godfrey, 2015; Tan, Godfrey, & Barker, 2009). The benefit of the technique is the straightforward processing at the system output. However, the typical method of ensuring orthogonality by modulation with the rows of a Hadamard matrix causes the required signal period to increase significantly. The required signal period is proportional to 2^{r-1}, where r is the number of inputs. The required signal period can be shortened by using a third approach which applies signals which are correlated with one another (Pinter & Fernando, 2010). A shortcoming of the correlated approach is that it requires an iterative procedure to estimate the impulse responses of the individual channels, due to the need to gradually remove the interfering terms resulting from the nonzero correlation between the inputs.

In cases where the system scales up to having a large number of inputs, the issues of long perturbation signal period (which is tied directly to the experimentation time) and processing time become bottlenecks which need urgent attention. In the area of communications, the European 5G project METIS identifies massive multi-input multi-output (MIMO) as a key 5G enabler and lists channel estimation as one of the essential issues that needs

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Nomenclature

r	number of inputs
i	index for input number or path number
n	time index
k	harmonic number
u_i	input to path i
g_i	impulse response of path i
y_i	$u_i * g_i$
U_i	DFT of u_i
G_i	DFT of g_i
Y_i	DFT of y_i
m	length of impulse response
N	signal period
ζ	set of excited harmonics
α	DFT of time domain window
f	frequency domain operator
η	additive output noise in the frequency domain

to be addressed (Fodor et al., 2017). Massive MIMO systems with more than 100 antennas are described in Rusek et al. (2013). In the area of medical imaging, ultrasound scanners with a large number of channels (such as 256 channels) have been developed in recent years for exploration of new methods (Boni et al., 2016; Liu et al., 2014). The correlated approach is best positioned to tackle the challenges due to scaling up as the identification test can be carried out in a single experiment and the requirement on signal period is less stringent than for the uncorrelated approach. Thus, in this paper, a novel identification technique is proposed to provide significant reduction on the required signal period, while maintaining similar computational complexity as the current state-of-the-art algorithm (Fernando, 2014) (henceforth referred to as the time-frequency swapping (TFS) algorithm). The main contributions of the paper are as follows:

(i) Formulation of a novel identification technique.
(ii) Derivation of the contributions of interfering terms and noise terms to the estimates.
(iii) New theorems relating to the estimates of the proposed algorithm.
(iv) Analysis of the computational complexity of the proposed algorithm.

The rest of the paper is organised as follows. The proposed identification technique is introduced in Section 2. Theoretical analysis is presented in Section 3. Two application examples are illustrated in Section 4. Finally, concluding remarks are drawn in Section 5.

2. Formulation of a novel identification technique

2.1. Notation and problem setting

A linear time-invariant sampled data system with r inputs and a single output is considered. Systems with multiple outputs can be catered for by combining several single-output systems. The impulse response from input i to the output is denoted by $g_i(n)$, where $1 \le i \le r$, and n represents the time index. The length of $g_i(n)$ is defined by m, such that $g_i(n) = 0\ \forall n \ge m$. The perturbation signals are applied simultaneously to the system such that u_i is the input to path i. The condition for persistent excitation is assumed to be satisfied. The output is given by $y = \sum_{i=1}^{r} y_i + w$, where w represents additive output noise and the intermediate signals $y_i = u_i * g_i$, with '$*$' denoting convolution, are assumed to be unavailable for identification. The signals y_i represent the effects of the individual inputs u_i on the output y. The objective is to estimate g_i through a single experiment based on the steady-state measurement of y. The problem is non-trivial due to the fact that the intermediate signals are unknown and the correlation between the inputs causes multiple access interference. The discrete Fourier transforms (DFTs) of $u_i(n)$, $g_i(n)$ and $y_i(n)$ are denoted by $U_i(k)$, $G_i(k)$ and $Y_i(k)$, respectively, where k represents the harmonic number.

2.2. Design of correlated signals

The set of perturbation signals u_i, $1 \le i \le r$, should satisfy the following conditions:

(i) The signals share a common period N.
(ii) The signals are correlated with one another such that they share the same excited harmonics defined by the set $\zeta = \{p | U_i(p) \ne 0, 0 \le p \le N-1, p \in \mathrm{Z}\}$ where Z is the set of all integers.
(iii) The signals have different phase realisations and the cross-correlation between any pair of signals is noiselike.
(iv) The signals are persistently exciting.

Remark 1. In the presence of nonlinear distortion in the system, the power at integer multiples of harmonics $\tilde{k}_1$, $\tilde{k}_2$,..., $\tilde{k}_{\hat{k}}$ may be set to zero in order to reduce or eliminate the effects of nonlinear distortion. The suppressed harmonics define the complement of ζ given by $\bar{\zeta} = S_{\tilde{k}_1} \cup S_{\tilde{k}_2} \cup \ldots \cup S_{\tilde{k}_{\hat{k}}}$, where $S_{\tilde{k}_\upsilon} = \{\tilde{k}_\upsilon, 2\tilde{k}_\upsilon, \ldots, N - \tilde{k}_\upsilon\}\ \forall \upsilon \in \{q | 1 \le q \le \hat{k}, q \in \mathrm{Z}\}$. This allows a linear framework to be adopted.

Remark 2. The power spectrum is not required to be uniform at all the excited harmonics. This allows the application of many classes of signals where the spectra are not perfectly uniform such as maximum length binary (Godfrey, Tan, Barker, & Chong, 2005), discrete interval binary and ternary (Schoukens, Pintelon, & Rolain, 2012), multi-level multi-harmonic (Tan and Godfrey, 2004b) and direct synthesis signals (Tan, 2013). This is particularly useful in situations where hardware limitations dictate the use of signals with a small number of levels. Some examples are described in Mohanty (2009), Roinila, Helin, Vilkko, Suntio, and Koivisto (2009) and Tan and Godfrey (2004a).

Remark 3. The signals should ideally have identical power spectrum $|U_i(k)|^2$ such that $|U_1(k)|^2 = |U_2(k)|^2 = \ldots = |U_r(k)|^2$. However, signals with non-identical power spectrum can be accommodated, at the expense of either a longer signal period or a longer processing time due to slower convergence of the algorithm.

2.3. Iterative algorithm

The iterative algorithm extracts the individual contributions of each input at the system output based on the steady-state measurement of y. At least one steady-state period is required. A summary of the steps is given below, where the subscript after the comma denotes the iteration number.

Step 1: Initialise the estimates at iteration 0 as

$$\hat{Y}_{i,0}(k) = Y(k),\ i \in \{1, 2, \ldots, r\}. \tag{1}$$

Step 2: Compute the estimates of the frequency response functions given by

$$\hat{G}_{i,0}(k) = \begin{cases} \hat{Y}_{i,0}(k)/U_i(k) & \forall k \in \zeta \\ 0 & \forall k \notin \zeta \end{cases}. \tag{2}$$