Combinatorial Characterization for Global Identifiability of Separable Networks with Partial Excitation and Measurement

Neuroscience [Chiêm et al. 2021] Power grids

Physiological models [Christie et al. 2014] Stock market [Shahzad et al. 2018]

Model

state
$$
\leftarrow
$$
 w = **Gw** + **Br** \longrightarrow excitation
measure \leftarrow **y** = **Cw**

From given excitations *r* at *B* and measurements *y* at *C*, can we recover the unknown transfer fcts *Gij* ?

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can we recover the unknown transfer fcts *Gij* ?

Framework: Not all nodes are excited/measured Handle known transfer functions No use of noise. But reformulation at [Shi, Cheng, Van den Hof 2019] Single frequency – scalar case Assumptions: Network topology is known Global transfer matrix *C* **(***I* **−** *G***) −**1 *B* is known $\overline{T(G)}$

Example state \leftarrow $w = Gw + Br \rightarrow$ excitation

measure **←−** *y* **=** *C w*

From given excitations *r* at *B* and measurements *y* at *C*, can we recover the unknown transfer fcts *Gij* ?

$$
G = \begin{bmatrix} 0 & 0 & G_{13} \\ G_{21} & 0 & G_{23} \\ G_{31} & 0 & 0 \end{bmatrix} \qquad C = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \end{bmatrix} \qquad B = \begin{bmatrix} 0 & 0 \\ 1 & 0 \\ 0 & 1 \end{bmatrix}
$$

$$
T \triangleq (I - G)^{-1} = \frac{1}{1 - G_{13}G_{31}} \begin{bmatrix} 1 & 0 & G_{13} \\ G_{21} + G_{31}G_{23} & 1 & G_{23} + G_{13}G_{21} \\ G_{31} & 0 & 1 \end{bmatrix}
$$

Example state \leftarrow $w = Gw + Br \rightarrow$ excitation

measure **←−** *y* **=** *C w*

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$$

Example

The question is:

From
$$
\mathbf{C} \mathbf{T} \mathbf{B} = \frac{1}{1 - G_{13} G_{31}} \begin{bmatrix} 1 & 0 & G_{13} \\ G_{21} + G_{31} G_{23} & 1 & G_{23} + G_{13} G_{21} \\ G_{31} & 0 & 1 \end{bmatrix}
$$
,

can we uniquely recover G₁₃ and G₂₃?

Outline

- 1. Introduction
- 2. Model
- 3. Identifiability
- 4. Algebraic characterization
	- \blacktriangleright Local identifiability
	- \blacktriangleright Decoupled identifiability
	- \blacktriangleright Separable networks
- 5. Combinatorial characterization
- 6. Conclusion

Does
$$
\underbrace{CTB}_{\text{known}} = C (I - G)^{-1} B
$$
 admit a unique solution G?

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All nodes excitated: Necessary and sufficient path-based condition $i.e. $B = I$$ [Hendrickx, Gevers, Bazanella 2017]

Algo allocating measurements in the graph

[Cheng, Shi, Van den Hof 2019]

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All nodes measured: Dual results

i.e. $C = I$

Does
$$
\underbrace{CTB}_{\text{known}} = C (I - G)^{-1} B
$$
 admit a unique solution *G*?

All nodes excitated: Necessary and sufficient path-based condition $i.e. B = I$ [Hendrickx, Gevers, Bazanella 2017] Algo allocating measurements in the graph [Cheng, Shi, Van den Hof 2019]

All nodes measured: Dual results $i.e. $C = I$$

General case: Our approach: we linearize

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From the definition of global identifiability...

Definition: Network globally identifiable at *G* if for all \tilde{G} :

$$
C T(\tilde{G}) B = C T(G) B \Rightarrow \tilde{G} = G
$$

... we introduce *local* identifiability

Definition: Network *locally* identifiable at *G* if for all *G*˜ *on an* ^ε**−***ball:*

$$
C T(\tilde{G}) B = C T(G) B \Rightarrow \tilde{G} = G
$$

Local identifiability is necessary

Definition: Network *locally* identifiable at *G* if for all *G*˜ *on an* ^ε**−***ball:*

 $C T(\tilde{G}) B = C T(G) B \Rightarrow \tilde{G} = G$

- \blacktriangleright Necessary for global identifiability
- \triangleright No counter-example to sufficiency known

Local identifiability is generic

Unformally, it does almost only depend on the graph topology.

Example: the nonzeroness of a polynomial is generic

When all nodes are excited/measured, **global** identifiability is also a generic property.

Algebraic characterization

Definition: Network *locally* identifiable at *G* if for all *G*˜ *on an* ^ε**−***ball:*

 $C T(\tilde{G}) B = C T(G) B \Rightarrow \tilde{G} = G$

- \blacktriangleright Necessary for global identifiability
- No counter-example to sufficiency known

 $W = K \triangleq (B^T T^T \otimes C T)I_G \Delta$ *^G*^Δ selects the columns corresponding to unknown transfer functions

Example

Theorem 1 (CDC 2020) G generically \Leftrightarrow $CT\Delta TB = 0 \Rightarrow \Delta = 0$ \Leftrightarrow *K* is full-rank locally identif $\forall \Delta$, generically generically

→→ Probability-1 algorithm: randomized, proba 0 of inaccuracy

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What we have so far

Global identifiability $C\tilde{T}B = CTB \Rightarrow \tilde{G} = G$ **⇓**

 \overline{G} Excitations Measurements

Local identifiability

*CT*Δ*TB* **=** 0 **⇒** Δ **=** 0

→ *Graph interpretation?*

Interpretation on a larger network

Global identifiability $C\tilde{T}B = CTB \Rightarrow \tilde{G} = G$ **⇓** Local identifiability *CT*Δ*TB* **=** 0 **⇒** Δ **=** 0

Decoupled identifiability

Global identifiability $C\tilde{T}B = CTB \Rightarrow \tilde{G} = G$ **⇓** Local identifiability *CT*Δ*TB* **=** 0 **⇒** Δ **=** 0 **⇓** Exc. Decoupled identifiability *CT*Δ*T* **′***^B* **⁼** ⁰ **[⇒]** ^Δ **⁼** ⁰

Decoupled network

Global identifiability of the decoupled network

Necessary... and sufficient?

Global identifiability $CTR = CTR \Rightarrow \tilde{G} = G$ **⇓ ⇑**? Local identifiability *CT*Δ*TB* **=** 0 **⇒** Δ **=** 0 **⇓ ⇑**? Decoupled identifiability *CT*Δ*T* **′***^B* **⁼** ⁰ **[⇒]** ^Δ **⁼** ⁰

No counter-example known

<github.com/alegat/identifiable>

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Separable networks

Generalization of the decoupled network:

Excited and measured subgraphs can now have different topologies

Proposition 2

On separable networks, local identifiability **⇔**global identifiability

⇒ Global identifiability can be studied via rank *K*

Other network topologies

The decoupled network is a particular case of separable network, where the excited and measured subgraph have same topology

⇒ Conditions derived for separable networks apply to decoupled identifiability

Reminder

Global Identifiability **⇒** Local Identifiability **⇒** Decoupled Identif

⇒ *Necessary* conditions derived for separable networks apply to global identifiability of *any* network topology

Summary

Global identifiability $CTB = CTB \Rightarrow G = G$ **⇓** Local identifiability *CT*Δ*TB* **=** 0 **⇒** Δ **=** 0 **⇓** Decoupled identifiability *CT*Δ*T* **′***^B* **⁼** ⁰ **[⇒]** ^Δ **⁼** ⁰

⇕

Global identifiability **⇐** Separable networks of the decoupled network (for which global **⇔**local)

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Framework

- ▶ *Global* identifiability on *separable* networks
	- **⇒** Applies on decoupled identifiability of all networks
- ▶ Identifiability of the *whole* network
- ▶ We assume: # unknowns = # excitations **×** # measurements
	- \Rightarrow Matrix *K* is now square, and: *K* full-rank \Leftrightarrow det *K* \neq 0

Theorem 2

A separable network is globally identifiable \Leftrightarrow det $K \neq 0$ generically **generically** generically

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Theorem 2

A separable network is globally identifiable \Leftrightarrow det $K \neq 0$
generically generically generically generically

det $K =$ $∑$ sign(*σ*) $□$ assignations σ *Gij TjbTci* (Leibniz)

 $=$ aei + bfg + cdh - ceg - afh - bdi

Lemma 1

The entries of $T(G) = (I - G)^{-1}$ are

$$
T_{ji} = \sum_{\substack{\text{all paths} \\ i \to j}} G_{j*} \ldots G_{*i}.
$$

*T*⁵¹ **=** *G*54*G*42*G*²¹ **+** *G*54*G*⁴¹ **+** *G*53*G*³¹

Take a collection of paths that link an excitation and a measurement to each unknown edge, bijectively.

A *monomial* μ is the product of all transfer functions of these paths

(where edges taken *n* times by the paths are to the power *n* in μ)

Two different collections of paths using the same transfer functions

⇒ Same monomial μ, but different sign in expression of det *K*

After algebra, we obtain

$$
\det K = \sum_{\mu \in M} r(\mu) \mu
$$

where

$$
\mu = \bigcap_{\text{all unknown edges } \alpha} G_{\text{measurement},\ast} \dots G_{\ast,\alpha} \cdot G_{\alpha,\ast} \dots G_{\ast,\text{excitation}}
$$

and the repetition $r(\mu)$ accounts for the sign of term μ in the expression of det *K*.

Theorem 3

A separable network is generically globally identifiable **⇔**there is at least one monomial $\mu \in M$ such that its repetition $r(\mu) \neq 0$

Future perspectives

- ▶ Path-based condition from our combinatorial characterization
- \blacktriangleright Algorithm for the synthesis problem
- \triangleright Gap between local and global identifiability
- \triangleright Gap between decoupled and local identifiability
- \blacktriangleright Path-based condition for single edge identifiability

Take-home message

- ▶ For identifiability: Global **⇒** Local **⇒** Decoupled
- ▶ Introduced *Separable networks,* for which Global **⇔**Local

- ▶ Necessary conditions derived on separable networks apply on networks of any topology, through the decoupled network
- ▶ Combinatorial *necessary and sufficient characterization*
- \blacktriangleright Further work:
	- Path-based condition from our combinatorial characterization
	- \blacktriangleright Algorithm for the synthesis problem

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Back-up slides

Model

 $\text{state} \longleftarrow w_i(t) = \sum G_{ij}(q) w_j(t)$ *g* is the shift operator, i.e. $q^{-1}w(t) = w(t-1)$

state
$$
\longleftarrow
$$
 $w_i(t) = \sum G_{ij}(q) w_j(t) + B_i r_i(t) \longrightarrow$ excitation
measure \longleftarrow $y_i(t) = C_i w_i(t)$ $B_i, C_i \in \{0, 1\}$

state
$$
\leftarrow
$$
 w = **G w** + **B r** \longrightarrow excitation
measure \leftarrow **y** = **C w**

Which nodes to excite/measure to recover the transfer functions? i.e. how to choose *B*, *C* to accurately recover *G*?

Transfer functions that can be recovered are *identifiable*

Network topology is defined by the nonzero entries of *G*, and is assumed to be known (often the case).

$$
G = \begin{bmatrix} G_{11} & 0 & G_{13} \\ G_{21} & 0 & G_{23} \\ G_{31} & 0 & 0 \end{bmatrix}
$$

Theorem: *Identifiability* is a generic property of *network topology*: it only depends* on the structure of *G*, but not on its parameters *Gij*.

Genericity

▶ A generic property holds everywhere except possibly on a *lower-dimensional set.*

▶ A lower-dimensional set has *Lebesgue-measure zero*

→ 0-probability of falling in this set when sampling randomly **Example:** The matrix

$$
A = \begin{bmatrix} x & 0 \\ 0 & x - y \end{bmatrix}
$$

has generic rank 2. Its rank drops on $\{x = 0\} \cup \{x = y\}$.

Identifiability is generic – example

Global input-output transfer function:

$$
CTB \triangleq C(I-G)^{-1}B = \begin{pmatrix} G_{42}G_{21} + G_{43}G_{31} & G_{42} & G_{43} & 1 & 0 \\ G_{52}G_{21} + G_{53}G_{31} & G_{52} & G_{53} & 0 & 1 \end{pmatrix}
$$

\n
$$
\Rightarrow G_{42}, G_{43}, G_{52}, G_{53} \text{ identif, and } \begin{pmatrix} G_{42} & G_{43} \\ G_{52} & G_{53} \end{pmatrix} \begin{pmatrix} G_{21} \\ G_{31} \end{pmatrix} = \begin{pmatrix} T_{41} \\ T_{51} \end{pmatrix}
$$

⇒ G_{21} , G_{31} identifiable except when $G_{42}G_{53} + G_{43}G_{52} = 0$.

