# Algebraic classification related to contrast optimization for MRI 

Bernard Bonnard ${ }^{1}$ Jean-Charles Faugère ${ }^{2}$ Alain Jacquemard ${ }^{2} \quad$ Mohab Safey El Din ${ }^{2}$ Thibaut Verron ${ }^{2}$

${ }^{1}$ Institut de Mathématiques de Bourgogne, Dijon, France UMR CNRS 5584
${ }^{2}$ Université Pierre et Marie Curie, Paris 6, France INRIA Paris-Rocquencourt, Équipe PoLSYs
Laboratoire d'Informatique de Paris 6, UMR CNRS 7606

Journées Nationales de Calcul Formel, 05 novembre 2015

## Physical problem

(N)MRI = (Nuclear) Magnetic Resonance Imagery

1. apply a magnetic field to a body
2. measure the radio waves emitted in reaction

Optimize the contrast = be able to distinguish two biological matters from this measure


Bad contrast
Good contrast
Known methods:

- inject contrast agents to the patient: potentially toxic
- make the field variable to exploit differences in relaxation times
$\Longrightarrow$ requires finding optimal settings
(Images: Pr. Steffen Glaser, Tech. Univ. München)


## Numerical approach

## The Bloch equations

$\left\{\begin{array}{l}\dot{y}_{i}=-\Gamma_{i} y_{i}-u_{x} z_{i} \\ \dot{z}_{i}=-\gamma_{i}\left(1-z_{i}\right)+u_{x} y_{i}\end{array}\right.$ $(i=1,2)$

## Saturation method

Find a path $u_{x}$ so that after some time $T$ :

- matter 1 saturated: $y_{1}(T)=z_{1}(T)=0$
- matter 2 "maximized": $\left|\left(y_{2}(T), z_{2}(T)\right)\right|$ maximal

Glaser's team, 2012 : Control Theory method

- Numerical method to find a path towards a saturated system = solution $u_{x}$
- Already used in some specific cases for the MRI, here applied in full generality


## Numerical approach... and computational problem

## The Bloch equations

$\left\{\begin{array}{l}\dot{y}_{i}=-\Gamma_{i} y_{i}-u_{x} z_{i} \\ \dot{z}_{i}=-\gamma_{i}\left(1-z_{i}\right)+u_{x} y_{i}\end{array}\right.$
$(i=1,2)$

## Saturation method

Find a path $u_{x}$ so that after some time $T$ :

- matter 1 saturated: $y_{1}(T)=z_{1}(T)=0$
- matter 2 "maximized": $\left|\left(y_{2}(T), z_{2}(T)\right)\right|$ maximal

Glaser's team, 2012 : Control Theory method

- Numerical method to find a path towards a saturated system = solution $u_{x}$
- Already used in some specific cases for the MRI, here applied in full generality Problem:
- The complexity of the path $u_{x}$ is not bounded


## Goal:

- Classify singular trajectories for the control
- Obtain control policies for the contrast problem

This classification problem can be modelled with polynomials!

## System

$-M:=\left(\begin{array}{cccc}-\Gamma_{1} y_{1} & -z_{1}-1 & -\Gamma_{1}+\left(\gamma_{1}-\Gamma_{1}\right) z_{1} & \left(2 \gamma_{1}-2 \Gamma_{1}\right) y_{1} \\ -\gamma_{1} z_{1} & y_{1} & \left(\gamma_{1}-\Gamma_{1}\right) y_{1} & 2 \Gamma_{1}-\gamma_{1}-\left(2 \gamma_{1}-2 \Gamma_{1}\right) z_{1} \\ -\Gamma_{2} y_{2} & -z_{2}-1 & -\Gamma_{2}+\left(\gamma_{2}-\Gamma_{2}\right) z_{2} & \left(2 \gamma_{2}-2 \Gamma_{2}\right) y_{2} \\ -\gamma_{2} z_{2} & y_{2} & \left(\gamma_{2}-\Gamma_{2}\right) y_{2} & 2 \Gamma_{2}-\gamma_{2}-\left(2 \gamma_{2}-2 \Gamma_{2}\right) z_{2}\end{array}\right)$

- $D:=\operatorname{det}(M)$


## Problem

Find all zeroes of $D$ which are singular in $\left(y_{1}, y_{2}, z_{1}, z_{2}\right)$

## Equivalent formulation

Find the zeroes of

$$
\left\langle D, \frac{\partial D}{\partial y_{1}}, \frac{\partial D}{\partial y_{2}}, \frac{\partial D}{\partial z_{1}}, \frac{\partial D}{\partial z_{2}}\right\rangle
$$

- Method described in [Bonnard et al. 2013]
- Proof of concept: they used this method to solve the problem for the 4 experimental settings serving as examples to the saturation method
- Question : solutions in full generality?


## Method

## Obvious method?

Compute a Gröbner basis of this system

- Works in theory: method used in [Bonnard et al. 2013]
- Impracticable in full generality

This work
Decompositic into simpler problems

- easy simplifications (e.g. $\gamma_{1}=1$ )
- specific physical cases: e.g. matter 1 is water $\Longleftrightarrow \Gamma_{1}=\gamma_{1}$
- specific structure of the system
- systematic study of factorizations


## What is "simpler"?

- More constraints: study $1+\langle f\rangle \Longleftrightarrow$ study $V(I) \cap V(f)$
- Less components: study $I+\langle U f-1\rangle \Longleftrightarrow$ study $V(I) \backslash V(f)$


## Method

## Obvious method?

Compute a Gröbner basis of this system

- Works in theory: method used in [Bonnard et al. 2013]
- Impracticable in full generality


## This work

Decomposition into simpler problems

- easy simplifications (e.g. $\gamma_{1}=1$ )
- specific physical cases: e.g. matter 1 is water $\Longleftrightarrow \Gamma_{1}=\gamma_{1}$
- specific structure of the system
- systematic study of factorizations


## What is "simpler"?

- More constraints: study $I+\langle f\rangle \Longleftrightarrow$ study $V(I) \cap V(f)$
- Less components: study $I+\langle U f-1\rangle \Longleftrightarrow$ study $V(I) \backslash V(f)$


## Method

## Obvious method?

Compute a Gröbner basis of this system

- Works in theory: method used in [Bonnard et al. 2013]
- Impracticable in full generality


## This work

Decomposition into simpler problems

- easy simplifications (e.g. $\gamma_{1}=1$ )
- specific physical cases: e.g. matter 1 is water $\Longleftrightarrow \Gamma_{1}=\gamma_{1}$
- specific structure of the system
- systematic study of factorizations


## Typical example

If $I$ contains $f \cdot g$, we can decompose the system into:

- either $f=0 \rightarrow$ add $f$ to the system
- or $f \neq 0$ and $g=0 \rightarrow$ add $U f-1$ and $g$ to the system


## First decomposition: rank of the matrix

We split the problem depending on the rank of the matrix:


Why the rank? Because of...

## Theorem

Consider

$$
M=\left(P_{i, j}(\mathbf{X})\right)_{1 \leq i, j \leq n}
$$

Then generically:

$$
\operatorname{det}(M) \text { singular } \Longrightarrow \operatorname{rank}(M)<n-1
$$

For our specific matrix, we do not know if the theorem applies.
$\Longrightarrow$ We need to consider both branches.

## First decomposition: rank of the matrix

We split the problem depending on the rank of the matrix:


Why the rank? Because of...

## Theorem

Consider

$$
M=\left(P_{i, j}(\mathbf{X})\right)_{1 \leq i, j \leq n}
$$

Then generically:

$$
\operatorname{det}(M) \text { singular } \Longrightarrow \operatorname{rank}(M)<n-1
$$

For our specific matrix, we do not know if the theorem applies.
$\Longrightarrow$ We need to consider both branches.

## The case $\operatorname{rank}(M)<3$ : classification

$$
\left\langle D, \frac{\partial D}{\partial y_{1}}, \frac{\partial D}{\partial y_{2}}, \frac{\partial D}{\partial z_{1}}, \frac{\partial D}{\partial z_{2}}, 3 \text {-minors of } M\right\rangle \text { contains } P=\sum_{d=0}^{4} a_{d}\left(\Gamma_{1}, \Gamma_{2}, \gamma_{2}\right) y_{2}^{2 d}
$$

We classify depending on the number of roots of $P$ in $Y_{2}=y_{2}^{2}$ :

- First bound: degree of $P$
- Need to handle multiple roots (for example using discriminants)



## First decomposition: rank of the matrix

We split the problem depending on the rank of the matrix:


Why the rank? Because of...

## Theorem

Consider

$$
M=\left(P_{i, j}(\mathbf{X})\right)_{1 \leq i, j \leq n}
$$

Then generically:

$$
\operatorname{det}(M) \text { singular } \Longrightarrow \operatorname{rank}(M)<n-1
$$

For our specific matrix, the theorem does not apply.
$\Longrightarrow$ We need to consider both branches.

## The case $\operatorname{rank}(M)=n-1$ : incidence varieties

## Theorem

Consider $M=\left(P_{i, j}(\mathbf{X})\right)_{1 \leq i, j \leq n}$ and let $\mathcal{I}$ be the incidence variety defined by

$$
\left[\begin{array}{l} 
\\
M
\end{array}\right] \cdot\left[\begin{array}{c}
\lambda_{1} \\
\vdots \\
\lambda_{n-1}
\end{array}\right]=\left[\begin{array}{c}
0 \\
\vdots \\
0
\end{array}\right]
$$

If $(\mathbf{x})$ is a point of $V(\operatorname{det}(M))$, then:

- there exists a non-zero vector $\Lambda=\left(\lambda_{i}\right)$ such that $(\mathbf{x}, \Lambda) \in \mathcal{I}$


## The case $\operatorname{rank}(M)=n-1$ : incidence varieties

## Theorem

Consider $M=\left(P_{i, j}(\mathbf{X})\right)_{1 \leq i, j \leq n}$ and let $\mathcal{I}$ be the incidence variety defined by

$$
\left[\begin{array}{l}
M
\end{array}\right] \cdot\left[\begin{array}{c}
\lambda_{1} \\
\vdots \\
\lambda_{n-1}
\end{array}\right]=\left[\begin{array}{c}
0 \\
\vdots \\
0
\end{array}\right]
$$

If $(\mathbf{x})$ is a singular point of $V(\operatorname{det}(M))$ such that $M(\mathbf{x})$ has rank $n-1$, then:

- there exists a non-zero vector $\Lambda=\left(\lambda_{i}\right)$ such that $(\mathbf{x}, \Lambda) \in \mathcal{I}$, and
- $\wedge$ is unique up to scalar multiplication, and
- $(\mathbf{x}, \Lambda)$ is a singular point of $\mathcal{I}$ w.r.t. $\mathbf{X}$


## The case $\operatorname{rank}(M)=n-1$ : incidence varieties

## Theorem

Consider $M=\left(P_{i, j}(\mathbf{X})\right)_{1 \leq i, j \leq n}$ and let $\mathcal{I}$ be the incidence variety defined by

$$
\left[\begin{array}{l}
M
\end{array}\right] \cdot\left[\begin{array}{c}
\lambda_{1} \\
\vdots \\
\lambda_{n-1}
\end{array}\right]=\left[\begin{array}{c}
0 \\
\vdots \\
0
\end{array}\right]
$$

If $(\mathbf{x})$ is a singular point of $V(\operatorname{det}(M))$ such that $M(\mathbf{x})$ has rank $n-1$, then:

- there exists a non-zero vector $\Lambda=\left(\lambda_{i}\right)$ such that $(\mathbf{x}, \Lambda) \in \mathcal{I}$, and
- $\Lambda$ is unique up to scalar multiplication, and
- $(\mathbf{x}, \Lambda)$ is a singular point of $\mathcal{I}$ w.r.t. $\mathbf{X}$



## Overview of the classification



More branches from factorizations

## Overview of the classification


$\operatorname{rank}(M)<3$
$Y_{2} \leftarrow y_{2}^{2}$
6 branches according to the number of roots of $P$

Branches according to the degree of $P$ and the roots multiplicity

## Conclusion, perspectives

## What has been done?

Classification of singular trajectories for the saturation control

- Exhaustive classification in some particular cases
- Some branches entirely explored in full generality


## Still work in progress

- Some branches not solved yet in full generality
- More physical constraints have to be taken into account
- Specific physical cases do not necessarily appear in the classification


## Applications

- Identification of the situations where the saturation method may fail
- New control policies trying to avoid these points


## Overview of the classification



$$
Y_{2} \leftarrow y_{2}^{2}
$$

6 branches according to the number of roots of $P$

Branches according to the degree of $P$ and the roots multiplicity

16 branches according to the nonzero minor

4 branches according to the non-zero coordinate in $\Lambda$

More branches from factorizations

More branches from factorizations

## Thank you for your attention! Merci pour votre attention!

