

Selective and Robust Time Optimal $SO(3)$ -Transformations

Séminaire Physique-Mathématiques, IMB

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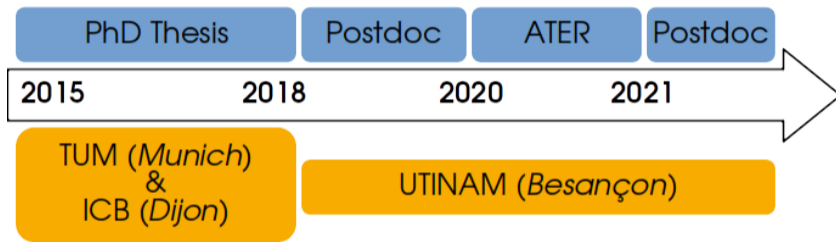
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FRANCHE-COMTÉ



Self introduction

Career :



PhD Thesis : Steffen Glaser & Dominique Sugny.

Postdocs / ATER : Bruno Bellomo, Dominique Sugny, David Viennot, José Lages, Dima Shepelyansky, Alexei Chepelianskii.

Fields of research

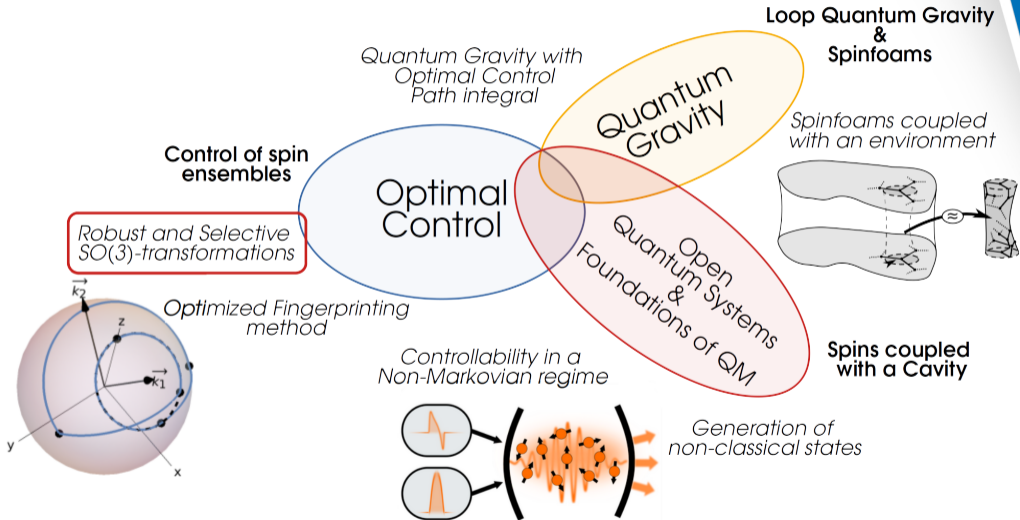


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Optimal Control of Spin-1/2 Particles: Motivations

Spin-1/2 particles and magnetization vector

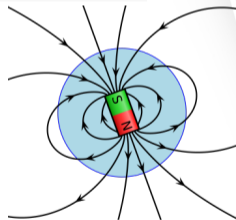
Spin-1/2 particle

A spin-1/2 particle can be considered as an "elementary magnetic dipole" (source of the magnetic field), which can be described (at least in our case study), by its magnetization vector $\vec{M} = (M_x, M_y, M_z) \in \mathbb{R}^3$.

Dynamics of a *single* spin-1/2 can be modeled using the Bloch equation (without relaxation):

$$\frac{d\vec{M}}{dt} = -\gamma \vec{B}(\vec{q}, t) \wedge \vec{M}(t).$$

With $\vec{B}(\vec{q}, t) \in \mathbb{R}^3$ a position and time dependent magnetic field, $\gamma \in \mathbb{R}_+$ is the gyromagnetic ratio, and \wedge denotes the vector cross product.



Spin-1/2 and applications

Behaviors of spin-1/2 systems (or 2 level quantum systems) are at the core of many technologies. For examples:

Magnetic Resonance Spectroscopy

Magnetic Resonance Imaging

Quantum Computing

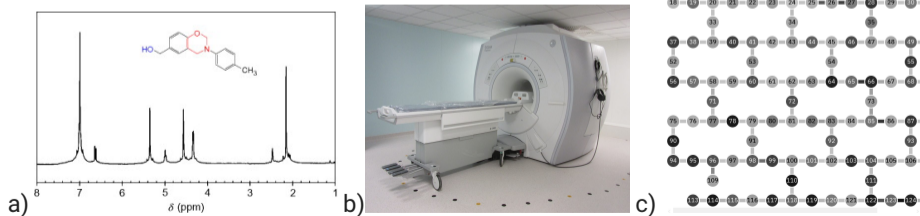
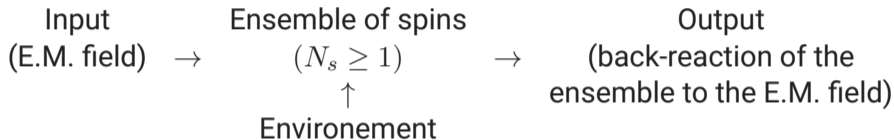


Figure 1: a) NMR spectrum b) a MRI scanner and c) Structure of IBM's 127-qubits processor.

Control of Spin-1/2 particles

Global idea:



Environment:

- decoherence
- Inhomogeneity of the physical parameters : resonance frequency, interaction strength,...

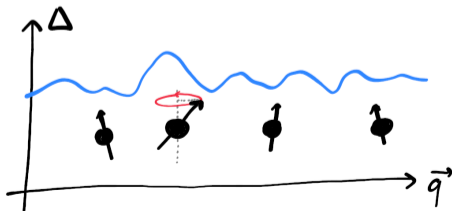
Usually, the environment reduces the fidelity of the output with respect to the expected/idealized result.

An example of inhomogeneity effect

In a given rotating frame, we can rewrite the Bloch equation into:

$$\frac{d\vec{M}}{dt} = - \begin{pmatrix} \omega_x(t, \vec{q}) \\ \omega_y(t, \vec{q}) \\ \Delta(\vec{q}) \end{pmatrix} \wedge \vec{M}(t).$$

with Δ the offset from a given frequency ω_z of reference. ω_x and ω_y are two control fields.



An example of inhomogeneity effect

- Bloch's equation:

$$\frac{d\vec{M}}{dt} = - \begin{pmatrix} \omega_x(t, \vec{q}) \\ \omega_y(t, \vec{q}) \\ \Delta(\vec{q}) \end{pmatrix} \wedge \vec{M}(t).$$

- We can perform simple rotations of the Bloch vector using ω_x and ω_y constant over a time interval.
- **Example:** for $\Delta = 0$, $\vec{M}(0) = (0, 0, 1)$, and using $\omega_x T = \pi/2$, $\omega_y = 0$, we have $\vec{M}(T) = (0, 1, 0)$. The solution is not robust against modifications of Δ .
- Square pulse
- Optimal pulse



Introduction to Optimal Control Theory

General statement

- Let us consider a system whose physical configuration (at time t) is modeled by a vector $x(t) = \{x^a(t)\}_{a=1..n} \in \mathbb{R}^n$, and is controlled by a control field $u(t) \in \mathbb{R}^m$.
- System dynamics are governed by the differential equation:

$$\frac{d}{dt}x^a(t) = f^a(x(t), u(t), t), \quad (1)$$

- The goal is to transform the initial state $x(0) = x_0$ into a target state x_{target} at $t = t_f \geq 0$, by using only the control field u , while minimizing one or several quantities, called *cost function* (or *figure of merit*).

General statement

Cost functions can be decomposed into two different categories:

Terminal cost

A function $h(x(t_f), t_f)$ that depends only on the final state.

Dynamical cost

A functional:

$$\int_0^{t_f} f_0(x(t), u(t), t) dt.$$

It can depend on the entire trajectory of x and u .

A general cost function is:

$$F = h(x(t_f), t_f) + \int_0^{t_f} f_0(x(t), u(t), t) dt. \quad (2)$$

General statement

Problem

How can we determine: $u^* = \min_u F$, such that $\frac{dx^a}{dt} = f^a(x, u, t)$?

Looks like classical mechanics! \rightarrow calculus of variation...

...but, we have a few differences:

- We have two quantities x and u , which are not treated exactly in the same manner.
- There is no natural canonical momentum \rightarrow "usual" Lagrangian may not be useful.

The "optimal control trick"

We consider an extended state of configuration $X = (x, \dot{x}, p, \dot{p}, u, \dot{u})$, where $p \in \mathbb{R}^n$ is called the adjoint state of x .

We define a Lagrangian $L(X(t))$, and an action S :

$$S = \int_{t_0}^{t_f} L(X) dt = \int_{t_0}^{t_f} dt [f_0(x, u, t) + p_a (\dot{x}^a - f^a(x, u, t))] \quad (3)$$

Note:

- Einstein's notation is used.
- p plays the role of Lagrange multipliers.
- By construction of L , we have extremums of S when $\dot{x}^a = f^a$.

See: M.Contreras, & al., 'Dynamic Optimization and Its Relation to Classical and Quantum Constrained Systems', *Physica A*, 479 (2017), for a detailed and pedagogical discussion.

Euler-Lagrange equations

Minimization of the action $S \rightarrow$ Computation of the first order variations of S from an arbitrary trajectory of reference.

Theorem 1

Let \mathbf{C} be the set of all curves $X : [t_i, t_f] \rightarrow \mathbb{R}^n$ of class C^2 . Let $\gamma \in \mathbf{C}$ be a *reference curve* with extremities $(t_0, x_0), (t_1, x_1)$. Let $\gamma' \in \mathbf{C}$ be *another* curve with extremities $(t_0 + \delta t_0, x_0 + \delta x_0), (t_1 + \delta t_1, x_1 + \delta x_1)$. We define $h(t) = \gamma'(t) - \gamma(t)$. Then, if we set $\Delta S = S(\gamma') - S(\gamma)$, we have:

$$\begin{aligned} \Delta S = & \int_{t_0}^{t_1} \left(\frac{\partial L}{\partial X^a} - \frac{d}{dt} \frac{\partial L}{\partial \dot{X}^a} \right)_{|\gamma} h^a dt + \left[\frac{\partial L}{\partial \dot{X}^a} \delta X^a \right]_{t_0}^{t_1} \\ & + \left[\left(L - \frac{\partial L}{\partial \dot{X}^a} \dot{X}^a \right)_{|\gamma} \delta t \right]_{t_0}^{t_1} + o^2(D(\gamma, \gamma')) \end{aligned}$$

With $D(\gamma, \gamma')$ a distance between the curves in \mathbf{C} .

Euler-Lagrange equations

We consider the case of fixed boundaries (i.e. $\delta X^a = 0$ and $\delta t = 0$).

Then, extremums of S , given by $\Delta S = 0$, are characterized by the Euler-Lagrange equation:

$$\frac{\partial L}{\partial X^a} - \frac{d}{dt} \frac{\partial L}{\partial \dot{X}^a} = 0.$$

Application to the O.C. Lagrangian:

$$\begin{cases} \frac{\partial L}{\partial x^a} - \frac{d}{dt} \frac{\partial L}{\partial \dot{x}^a} = 0 \\ \frac{\partial L}{\partial p_a} - \frac{d}{dt} \frac{\partial L}{\partial \dot{p}_a} = 0 \\ \frac{\partial L}{\partial u^c} - \frac{d}{dt} \frac{\partial L}{\partial \dot{u}^c} = 0 \end{cases} \Rightarrow \begin{cases} \dot{p}_a = \frac{\partial}{\partial x^a} (f_0 - f^b \delta^a_b) \\ \dot{x}^a = f^a \\ \frac{\partial f_0}{\partial u^c} = p_b \frac{\partial f^b}{\partial u^c}. \end{cases} \quad (4)$$

The equation $\frac{\partial f_0}{\partial u^c} = p_b \frac{\partial f^b}{\partial u^c} \longrightarrow$ allows us to determine $u(t) = u(x(t), p(t))$.

Hamiltonian formalism

Equivalently, we can use the Hamiltonian formalism:

Hamiltonian

$$\begin{aligned}
 H_p &= P_a \dot{X}^a - L \\
 &= p_a f^a - f_0 + p_{u,c} \dot{u}^c,
 \end{aligned}$$

with $p_{u,c}$ the adjoint state of the control field, that we can set to 0 in our case, because there is no constraint of the form $\dot{u}^c = \dots$

Hamilton's equations

$$\frac{\partial H_p}{\partial X^a} = -\dot{P}_a ; \quad \frac{\partial H_p}{\partial P^a} = \dot{X}^a$$

Hamiltonian formalism

The correspondence between the equations of dynamics is then:

$$\left\{ \begin{array}{l} \frac{\partial L}{\partial x^a} - \frac{d}{dt} \frac{\partial L}{\partial \dot{x}^a} = 0 \\ \frac{\partial L}{\partial p_a} - \frac{d}{dt} \frac{\partial L}{\partial \dot{p}_a} = 0 \\ \frac{\partial L}{\partial u^c} - \frac{d}{dt} \frac{\partial L}{\partial \dot{u}_c} = 0 \end{array} \right. \Leftrightarrow \left\{ \begin{array}{l} \frac{\partial H_p}{\partial x^a} = -\dot{p}_a \\ \frac{\partial H_p}{\partial p_a} = \dot{x}_a \\ \frac{\partial H_p}{\partial u^c} = 0 \end{array} \right. \Rightarrow \left\{ \begin{array}{l} \dot{p}_a = \frac{\partial}{\partial x^a} (f_0 - f^b \delta^a_b) \\ \dot{x}^a = f^a \\ \frac{\partial f_0}{\partial u^c} = p_b \frac{\partial f^b}{\partial u^c} \end{array} \right.$$

Theorem 2

Weak Pontryagin Minimum (Maximum) Principle (**PMP**) :

$$\frac{\partial H_p}{\partial u^c} = 0.$$

The case of bounded control fields

In the case where the control field is in
 $U \subset \mathbb{R}^m$

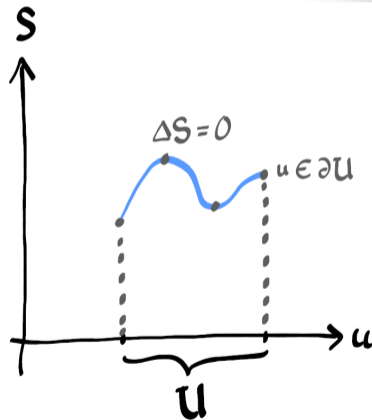
Theorem 3

The general PMP :

$$\frac{\partial H_p}{\partial u^c} = 0$$

or

$$u(t) \in \partial U.$$



Summary

- Control field \rightarrow generalized coordinates.
- Introduce the adjoint state p .
- Extremums of the action \rightarrow equations of dynamics in the extended space of configurations.
- The PMP provides constraints on the control field, which can be expressed as a function of the state x and its adjoint state p .

Optimization problem \rightarrow analysis of trajectories of a classical dynamical system.

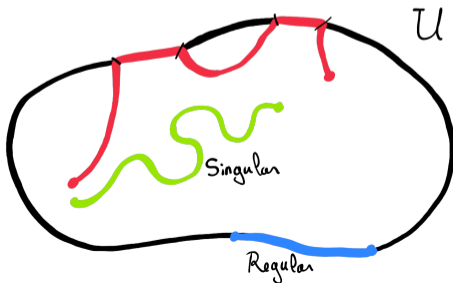
Classification of trajectories

Singular trajectory

The trajectory of the extended system X is said singular on $I = [t_1, t_2]$ if $\frac{\partial H_p}{\partial u^c} = 0 \forall t \in I$.

Regular trajectory

The trajectory of the extended system X is said regular on $I = [t_1, t_2]$ if $u(t) \in \partial U \forall t \in I$.





Selective and Robust Time Optimal $SO(3)$ Transformations

SO(3) transformations

Due to the cross product in the Bloch equation, we have $\vec{M}(t) = \hat{U}(t)\vec{M}(0)$ and $\hat{U}(t) \in SO(3)$.

$\hat{U}(t)$ is the solution of the differential equation:

$$\begin{aligned} \frac{d\hat{U}(\Delta, t)}{dt} &= \begin{pmatrix} 0 & \Delta & -\omega_y(t) \\ -\Delta & 0 & \omega_x(t) \\ \omega_y(t) & -\omega_x(t) & 0 \end{pmatrix} \hat{U}(\Delta, t) \\ &= (\omega_x(t)\hat{e}_x + \omega_y(t)\hat{e}_y + \Delta\hat{e}_z) \hat{U}(\Delta, t), \\ \hat{U}(\Delta, 0) &= \hat{\mathbb{I}}, \end{aligned} \tag{5}$$

- $\Delta \in \mathbb{R}$ is the frequency offset (resonance at $\Delta = 0$).
- $\omega_x(t) \in \mathbb{R}$ and $\omega_y(t) \in \mathbb{R}$ are two control fields such that $\omega_x(t)^2 + \omega_y(t)^2 \leq \omega_0^2$.
- \hat{e}_x , \hat{e}_y and \hat{e}_z are generators of the $\mathfrak{so}(3)$ algebra.
- $\hat{\mathbb{I}}$ is the identity matrix.

The control problem

$$\begin{aligned} \frac{d\hat{U}(\Delta, t)}{dt} &= (\omega_x(t)\hat{e}_x + \omega_y(t)\hat{e}_y + \Delta\hat{e}_z)\hat{U}(\Delta, t), \\ \hat{U}(\Delta, 0) &= \hat{\mathbb{I}}, \end{aligned} \quad (6)$$

- At resonance ($\Delta = 0$) we would like to produce a transformation of the form $\hat{U}_{target}(0) = e^{\phi\hat{e}_x}$ at the final time T .
- For $\Delta \neq 0$, we have in general $\hat{U}(\Delta, T) \neq e^{\phi\hat{e}_x}$.

To quantify the selectivity or robustness of a control field, we introduce the following fidelity function:

$$F(\Delta) = \|\hat{U}(\Delta, T, \omega_x, \omega_y) - \hat{U}_{target}(\Delta = 0)\|^2, \quad (7)$$

where $\|\cdot\|$ is the Frobenius norm.

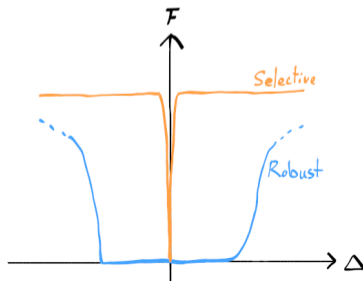
The control problem

Robust transformation

A transformation is said "robust" on the interval $I = [\Delta_a, \Delta_b]$ if for all $\Delta \in I$, $F(\Delta) \leq \varepsilon$, with ε quantifying the maximum permissible error.

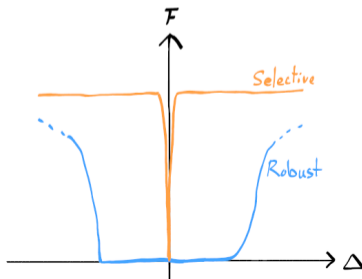
Selective transformation

A transformation is said "selective" if it produces the desired \hat{U}_{target} at $\Delta = 0$, and leaves the system unchanged for $\Delta \neq 0$, i.e. $\hat{U}(\Delta, T) \approx \hat{\mathbb{I}}$ for $\Delta \neq 0$.



State-of-the-art approach

1. Discretize the Δ axis, specify a target state $\hat{U}_{target}(\Delta)$ at each discretization point, and solve the optimal control problem simultaneously for all the points. *This requires (in general) a lot of points.*
2. Taylor expand F , and cancel the first-order derivatives around a specific value of Δ , i.e. $\frac{\partial^n F}{\partial \Delta^n} |_{\Delta=\Delta'} = 0, n = 1, 2, \dots, n_{max}$. *Works well for robust controls, less for selective ones.*



A novel approach

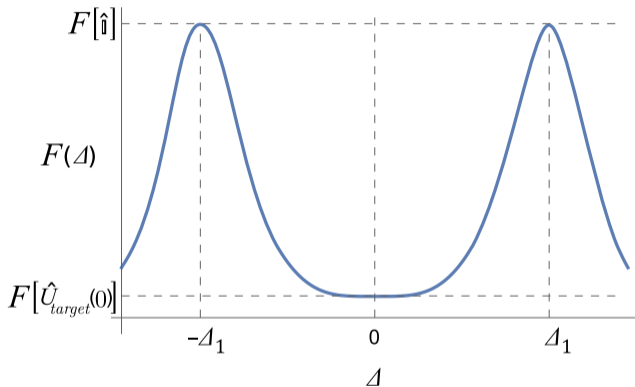
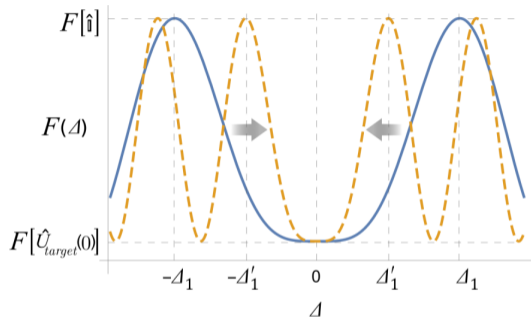


Figure 2: Example of fidelity function

$$F(\Delta) = \|\hat{U}(\Delta, T, \omega_x, \omega_y) - \hat{U}_{target}(\Delta = 0)\|^2$$

(8)

A novel approach



As a first approximation, we can focus on **only two offsets**: $\Delta = 0$, and $\Delta = \Delta_1$.
The target states are:

$$\hat{U}_{target}(0) = e^{\phi \hat{\epsilon}_x} ; \hat{U}_{target}(\Delta_1) = \hat{\mathbb{I}}. \quad (9)$$

The position of Δ_1 sets the level of robustness/selectivity of the control sequence.

Definition of OC quantities

The terminal cost function is $C = \frac{1}{6} \sum_{n=1}^2 \|\hat{U}_n(T, \omega_x) - \hat{U}_{n,target}\|^2$.

The dynamical cost function is: $\int_0^T dt = T$.

The Hamiltonian is:

$$H_p = \sum_{n=1}^2 \langle \hat{P}_n | \omega_x \hat{\epsilon}_x + \Delta_{(n)} \hat{\epsilon}_z | \hat{U}_n \rangle.$$

- \hat{P}_n is a 3×3 matrix, which is the adjoint state of \hat{U}_n .
- $\langle A|B \rangle = \text{Tr}[A^\top B]$ is the matrix scalar product.
- **For symmetry reasons, we can set $\omega_y = 0$, and keep only a single control ω_x .**

Structure of trajectories

Proposition 1

Singular trajectories S are given by constant controls of amplitude $|\omega_S| < \omega_0$.

Proposition 2

Regular trajectories are given by piecewise constant control fields of amplitude $\pm\omega_0$, with switchings when $l_x = \sum_{n=1}^2 \langle \hat{P}_n | \hat{\epsilon}_x | \hat{U}_n \rangle = 0$.

A constant part of a regular trajectory is called "a bang" B.

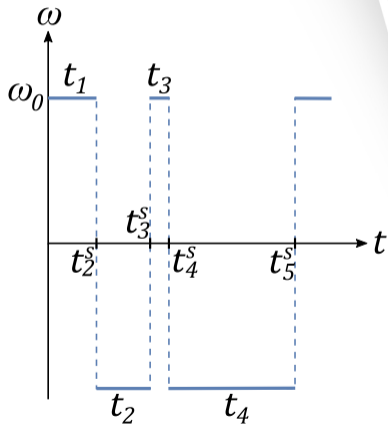


Figure 3: Structure of a regular control field with several switchings.

General expression of \hat{U}

Because the control field is piecewise constant, we have:

$$\hat{U}(T) = \prod_{j=1}^{N_p} e^{(\omega_j \hat{e}_x + \Delta \hat{e}_z) t_j}, \quad \omega_j \in [-\omega_0, \omega_0], \quad t_j > 0. \quad (10)$$

In the case of a single singular trajectory, we have:

$$\hat{U}(\Delta, T_S) = e^{T_S(\omega_S \hat{e}_x + \Delta \hat{e}_z)}, \quad (11)$$

and the target states are reached if:

$$\begin{cases} T_S \omega_S = \phi \\ T_S \sqrt{\omega_S^2 + \Delta_1^2} = 2k\pi, \quad k \in \mathbb{N}. \end{cases} \quad (12)$$

We define Δ_0 , the smallest solution of (12), such that $\omega_S = \omega_0$. And we denote by T_0 the corresponding control duration.



Selective Time Optimal Transformations

Selective Time Optimal transformations

Due to the specific structures of the trajectories, **we define selective controls such that:** $\Delta_1 \leq \Delta_0$. At the opposite $\Delta_1 \geq \Delta_0$ is used for robust controls.

Proposition 3

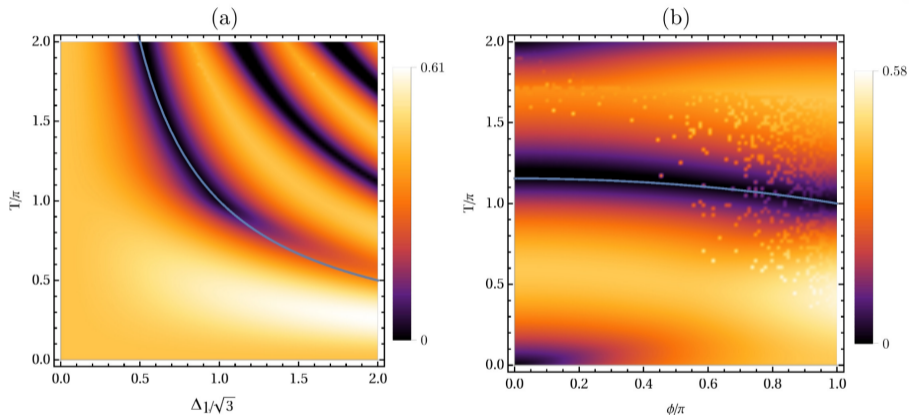
In the selective case, the following trajectories are not time-optimal:

- $B - B$
- $B - B - B$
- $B - B - B - B$
- $S - B$
- $B - S - B$
- $B - \dots - B - S - \dots$

Conjecture 1

Time-optimal **selective** transformations are given by **singular** trajectories S of Pontryagin's Hamiltonians.

Selective Time Optimal transformations



(a): C as a function T and Δ_1 , for a selective rotation of angle $\phi = \pi$ and $\omega_0 = 1$. (b): C as a function of T and ϕ . We set $\omega_0 = 1$ and $\Delta_1 = \sqrt{3}$. In the two cases, each point of the contour plot corresponds to a numerical optimization. Blue solid lines are defined by the equation $\Delta_1 = \sqrt{4\pi^2 - \phi^2}/T_S$.



Robust Time Optimal Transformations

Robust Time optimal transformations

We consider $\Delta_1 > \Delta_0$

Time-optimal robust transformations

Time optimal **robust** transformations are given by **regular** trajectories.

For a regular control, the general form of \hat{U} is:

$$\hat{U}(T) = \prod_{j=1}^{N_p} e^{(\omega_j \hat{e}_x + \Delta \hat{e}_z) t_j}, \quad \omega_j = \pm \omega_0, \quad t_j > 0.$$

Calculations can be performed for a small number of switchings (i.e., $N_p = 2, 3$).

1-switching regular controls

- Using the the fact that $\hat{U}_{target}(0) = e^{\phi \hat{e}_x}$ and $\hat{U}_{target}(\Delta_1) = \hat{\mathbb{I}}$, we can determine the durations t_1 and t_2 of each bang:

$$t_1 = t_2 + \frac{\phi}{\omega_0} ; t_2 = \frac{\phi}{2\omega_0} \left(\frac{n}{k} - 1 \right)$$

- The pulses are then parameterized by two integers: n and k .

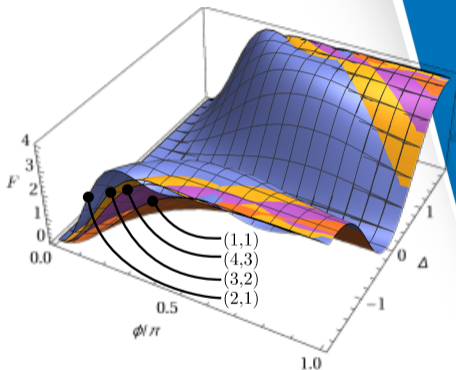


Figure 4: Fidelity of 1-switching controls for different (n, k) .

2-switchings regular controls

- Similarly, we can determine the duration t_1, t_2 and t_3 of each bang:

$$t_1 + t_3 = \frac{\phi}{\omega_0} \left(\frac{n}{k} - 1 \right) ; t_1 = \alpha t_3 ;$$

$$t_2 = (t_1 + t_3) + \phi/\omega_0$$

- The pulses are then parameterized by two integers: n and k , and one real parameter α .
- Using $\frac{\partial^2 F}{\partial \Delta^2}(0) = 0$, we can find the optimal α . For $\phi = \pi, \alpha = 1$.

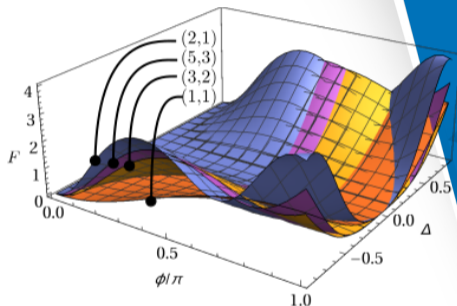


Figure 5: Fidelity of 2-switching controls for different (n, k) , and $\alpha = 1$.

2-switchings regular controls

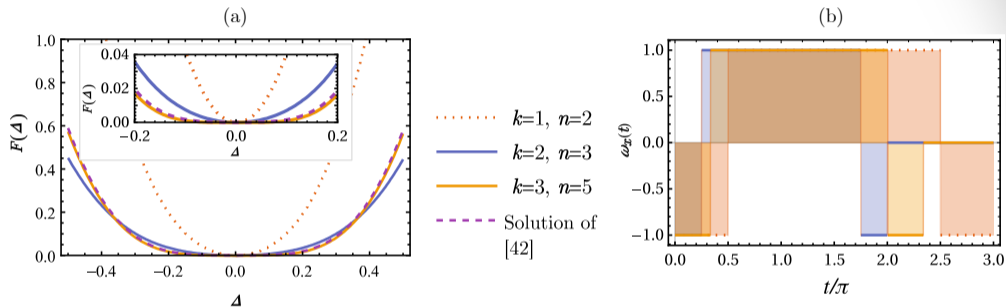


Figure 6: (a) Fidelity function F for a π -pulse for different values of (n, k) , and for the solution of [42] (obtained with a numerical optimization). The inset shows F near $\Delta = 0$. (b) Control field associated with each solution. Control times are respectively: $3\pi, 2\pi, 2.34\pi, 2.34\pi$ (top to bottom in the legend).



Conclusion

Conclusion

- Design of selective and robust $SO(3)$ -transformations.
- Computations are based on a model of two matrices of rotation, associated with two different offsets.
- Time optimal selective transformations are given by constant control fields of amplitude $|\omega_S| < \omega_0$.
- Robust transformations are given by regular "bang-bang" control fields parameterized by a few parameters. It is then easy to find a "good solution".

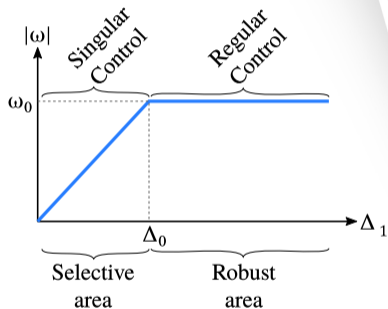


Figure 7: Transition from the area of selective controls characterized by singular solutions of the PMP, to the area of robust controls characterized by regular trajectories.

Outlook

- Using a larger number of offset can improve the selectivity or the robustness.
- For example, we can use the offsets: $0, \Delta_1, \Delta_2$ such that the target states are: $e^{\phi \hat{\epsilon}_x}, \hat{\mathbb{I}}, \hat{\mathbb{I}}$.
- With these more elaborated systems, no analytical expression of the optimal pulses is known in general.

The results presented in this talk are published in: Quentin Ansel & al, J. Phys. A: Math. Theor. 54 085204, 2021.