

# Super-Resolution in several dimensions and some applications

M. Velasco, M. Junca, C. Hernández, H. García

February 13, 2019

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# The Problem

- Consider the discrete positive measure

$$\mu := \sum_{i=1}^k c_i \delta_{x_i}, \quad c_i > 0$$

$$x_j \in X \subseteq \mathbb{R}^n.$$

- “Measurements” of the measure can be thought as

$$y_j := \int \Phi_j d\mu, \quad j = 1, \dots, m,$$

for some functions  $\Phi_j$ ,  $j = 1, \dots, m$  which are known or can be estimated.

The goal of super-resolution process is to recover  $\mu$   
knowing **ONLY**  $y_j$  and  $\Phi_j, j = 1, \dots, m$ .

# Applications

# Cubature Formulas

- In  $\mathbb{R}$ , a **cubature formula** is a way to approximate the integral  $\int_a^b f(t)dt$ .
- The integral is approximated as

$$\int_a^b f(t)dt \approx \sum_{i=1}^n w_i \cdot f(t_i),$$

for  $a \leq t_1 < \dots < t_n \leq b$ ,  $w_i > 0$ .

A classical result:

## Theorem

If we take  $t_1, \dots, t_n$  as the roots of the Legendre polynomial  $P_n$  and  $w_i$  as

$$w_i := \frac{2}{(1 - t_i^2) \cdot [P_n'(t_i)]^2},$$

then

$$\int_{-1}^1 q(t) dt = \sum_{i=1}^n w_i \cdot q(t_i)$$

for any polynomial  $q$  of degree lesser or equal to  $2n - 1$ .



- A cubature formula, in the sense of last Theorem, can be interpreted as a discrete measure

$$\mu := \sum_{i=1}^n w_i \cdot \delta_{t_i},$$

for  $a \leq t_1 < \dots < t_n \leq b$ ,  $w_i > 0$ , such that

- 

$$\int_{-1}^1 q(t) dt = \int_{-1}^1 q(t) d\mu,$$

for any polynomial  $q$  with degree lesser or equal to  $2n - 1$ .

- This condition is equivalent to claim

$$\int_{-1}^1 m dt = \int_{-1}^1 m d\mu,$$

for any monomial  $m$  with degree lesser or equal to  $2n - 1$ .

# Control Theory

- A control problem typically has the form

$$\min_{u(t)} \int_{[0, T]} h(t, x(t), u(t)) dt + H(x(T))$$

s.t

$$\frac{dx}{dt} = f(t, x(t), u(t)),$$

for  $u(t), x(t) \in C^\infty([0, T])$ ,  $x(t) \in X$ ,  $u(t) \in U$ ,  $x(0) = x_0$ .

- In general are not so easy: proposed solutions depend of structure of functions  $h(t, x, u)$ ,  $H(x)$  and simplifications of dynamic  $\frac{dx}{dt} = f(t, x(t), u(t))$ .

## Special case

- If both  $h, H$  are equal to zero and  $f := f(t, x(t))$ , control problem is a dynamical system.
- For example: height  $y$  of a ball falling has equations

$$\begin{pmatrix} \dot{y} \\ \dot{v} \end{pmatrix} = \begin{pmatrix} v \\ -g \end{pmatrix},$$

making substitution  $\dot{y} = v$ .

- Henrion suggests re-write the given control problem as

$$\min_{\substack{\mu \in M^+([0, T] \times X \times U), \\ \mu_F \in M^+(X)}} \int_{[0, T] \times X \times U} h(t, x, u) d\mu + \int_X H(x) d\mu_F$$

s.t

$$\int_X v(T, x) d\mu_F v(0, x(0)) = \int_{[0, T] \times X \times U} \left( \frac{\partial v}{\partial t} + \frac{\partial v}{\partial x} \right) f(t, x, u) d\mu,$$

for all  $v \in C^1([0, T] \times X)$ .

- Important issue: Any optimum measure  $\mu$  has as support the curve  $(t, x(t), u(t))$ ,  $t \in [0, T]$ .
- This is a problem with **INFINITE** restrictions!
- We can get a relaxation considering the functions  $v$  JUST as monomials up to degree  $d$ .

- Assume  $m_1, \dots, m_n$  the list of monomials with degree lesser or equal to some big enough  $d$ .
- - $h = \sum_{i=1}^n h_i \cdot m_i,$
  - $H = \sum_{i=1}^n H_i \cdot m_i,$
  - $f = \sum_{i=1}^n f_i \cdot m_i,$
  - $(\frac{\partial m_j}{\partial t} + \frac{\partial m_j}{\partial x})f(t, x, u) = \sum_i F_{ij} \cdot y_i,$
  - $h_i, H_i, f_i, F_{ij} \in \mathbb{R}.$
- Consider  $y_i := \int_{[0, T] \times X \times U} m_i \, d\mu$  and  $z_i := \int_X m_i \, d\mu_F.$

- With relaxation considering just monomials the problem results

$$\min_{H_y(d), H_z(d) \succeq 0} \sum_i h_i \cdot y_i + \sum_i H_i \cdot z_i$$

s.t

$$z_j - m_j(0, x(0)) = \sum_i F_{ij} \cdot y_i,$$

- This problem is **SEMIDEFINITE!!**.
- We can get the values  $y_i$  (Lasserre's method of Moments) and from that we want to recover measures  $\mu$  and  $\mu_F$ , in order to see their support.

# Results

In order to recover  $\mu$  from the values  $y_i$  consider the problem

$$\min_{\Delta} \|\Delta\|_{TV} \quad \text{s.t} \quad \int \Phi_i d\Delta = y_i. \quad (1)$$



## The seminal result

### Theorem (Gamboa, De Castro)

If  $\mu$  is a discrete positive measure supported at  $X \subseteq [-1, 1]$ ,  
 $|X| = k$ , and

$$\int x^i d\mu = y_i, \quad i = 0, \dots, n,$$

then  $\mu$  is the unique minimizer of Problem ( 1 ), for  $2n \geq k$ .

## Our Result

### Theorem

If  $\mu$  is a discrete positive measure supported at  $X \subseteq K \subseteq \mathbb{R}^n$ ,  $K$  compact and  $|X| = k$ , and

$$\int \Phi \, d\mu = y_i,$$

where  $\Phi_1, \dots, \Phi_m$  are the monomials in  $n$  variables up to degree  $d$ , then  $\mu$  is the unique minimizer of Problem ( 1 ), for  $d \geq \max(2g(X), i(X))$

- $g(X), i(X)$  are numbers depending of the algebraic structure of  $X$ .

The main idea of the proof in Theorem 3 is the existence of a **dual certificate**:

## Definition

A dual certificate is a polynomial  $P$  such that

- $0 \leq P(x) \leq 1$  for  $x \in K$ .
- $P(x) = 1$  iff  $x \in X$ .

A dual certificate  $P(x)$  recognizes the support of  $\mu!$ .

## Algorithm: Semidefinite Relaxation

- 1 Find a dual certificate  $P = 1 - \frac{H}{M}$  solving the problem:

$$\min_H \int_K H \, d\mu$$

s.t

$$H = \sum h_i^2, \quad \deg(h_i) \leq d, \quad H \neq 0.$$

- 2 Find support  $X$  of  $\mu$  as the maximum points of  $P$ .
- 3  $\mu = \sum_{x \in X} c_x \cdot \delta_x$ , so find the values  $c_x$  solving the linear system of equations

$$\sum_{x \in X} c_x \Phi_i(x) = y_i, \quad i = 1, \dots, m.$$

If signal measurements  $(y_1, \dots, y_m)$  are contaminated with some unknown noise  $\epsilon = (\epsilon_1, \dots, \epsilon_m)$  but such that  $\|\epsilon\| \leq \delta$ , the following problem is proposed to recover  $\mu$ :

$$\min_{\nu \in \mathcal{S}(K)} \|\nu\|_{\text{TV}} : \left\| \left( \int_K \phi_i d\nu - y_i \right)_{i=0, \dots, m} \right\|_2 \leq \delta \quad (2)$$

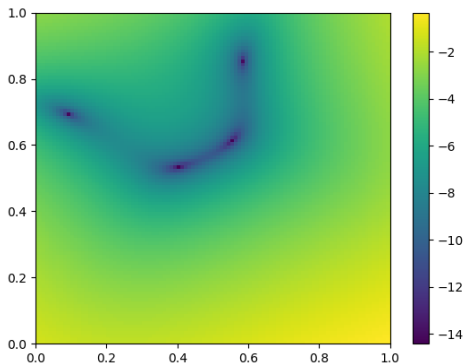
## Theorem

Let  $\hat{\Delta}$  be a discrete minimizer of (2) with  $V$  the vector space of polynomials up to degree  $d$ ,  $y_i := \int \phi_i d\mu + \epsilon_i$  and  $\|(\epsilon_i)_i\|_2 \leq \delta$ . If  $d \geq 2g(X)$  and  $\phi_0, \dots, \phi_m$  are an orthonormal basis for  $V$  with respect to some probability measure on  $K$  then  $\hat{\Delta}$  is “near” of  $\mu$  in the following sense:

- Assuming  $Y$  as the support of  $\hat{\Delta}$ , if  $y \in Y$  is “near” of  $X$ , coefficient of  $\delta_y$  is big.
- Otherwise its coefficient is little.

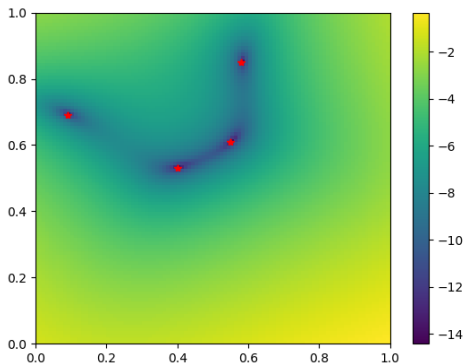
# Some Experiments

## Measure with 4 support points

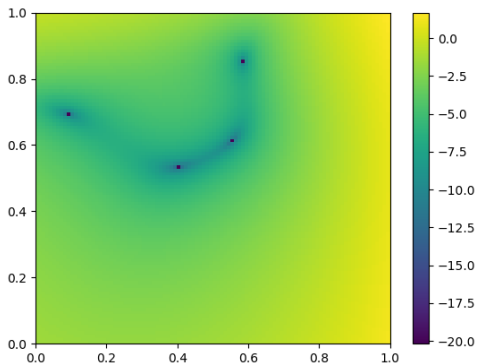




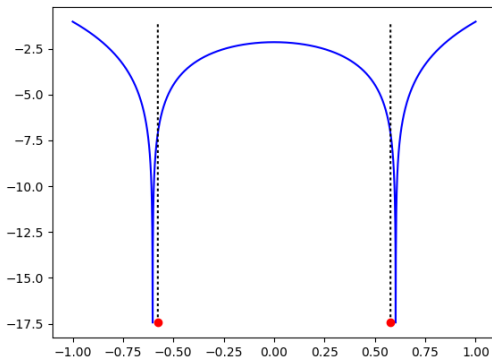
## Measure with 4 support points



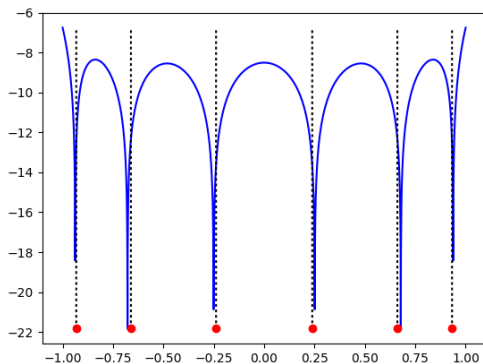
## Measure with 4 support points



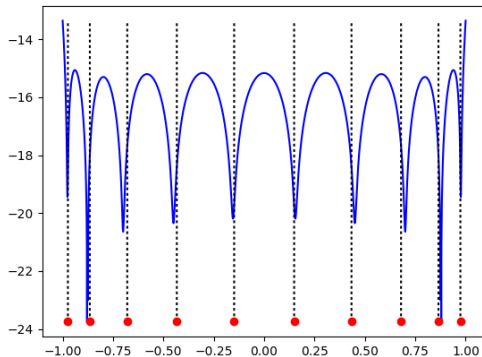
## Zeroes of $H = M(P + 1)$ , $d = 2$



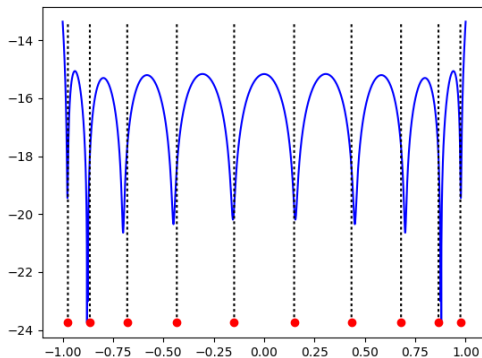
## Zeroes of $H = M(P + 1)$ , $d = 6$



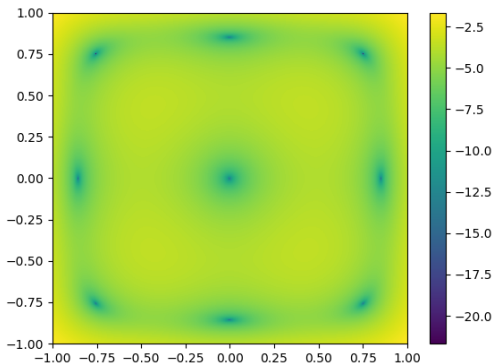
## Zeroes of $H = M(P + 1)$ , $d = 10$



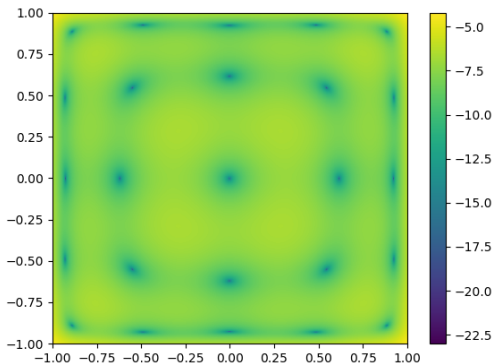
## Zeroes of $H = M(P + 1)$ , $d = 10$



## Zeroes of $H = M(P + 1)$ , $d = 3$

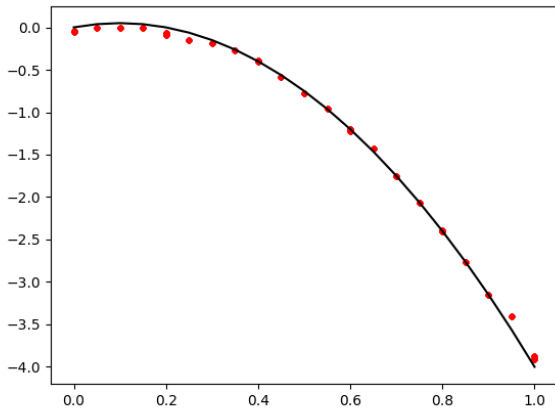


## Zeroes of $H = M(P + 1)$ , $d = 5$

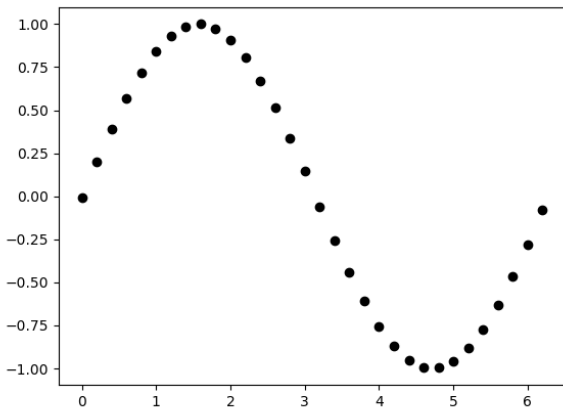







# Ball Falling



## Spring with mass



-  Didier Henrion, Jean B. Lasserre, Carlo Savorgnan *Nonlinear optimal control synthesis via occupation measures*, Proceedings of the 47th IEEE Conference on Decision and Control (2008)
-  Yohann de Castro, Fabrice Gamboa, *Exact reconstruction using Beurling minimal extrapolation*, J. Math. Anal. Appl. 395 (2012), no. 1, 336–354, DOI 10.1016/j.jmaa.2012.05.011. MR2943626
-  Mauricio Velasco, Mauricio Junca, Camilo Hernández, Hernán García *Approximate super-resolution and truncated moment problems in all dimensions*, eprint arXiv:1809.05994 (2018)