

A new method to compute the probability of collision for short-term space encounters

R. Serra, D. Arzelier, M. Joldes, J-B. Lasserre, A. Rondepierre and B. Salvy

Journées Nationales de Calcul Formel
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Fiction...



Credit Gravity (2013)

On-orbit collision

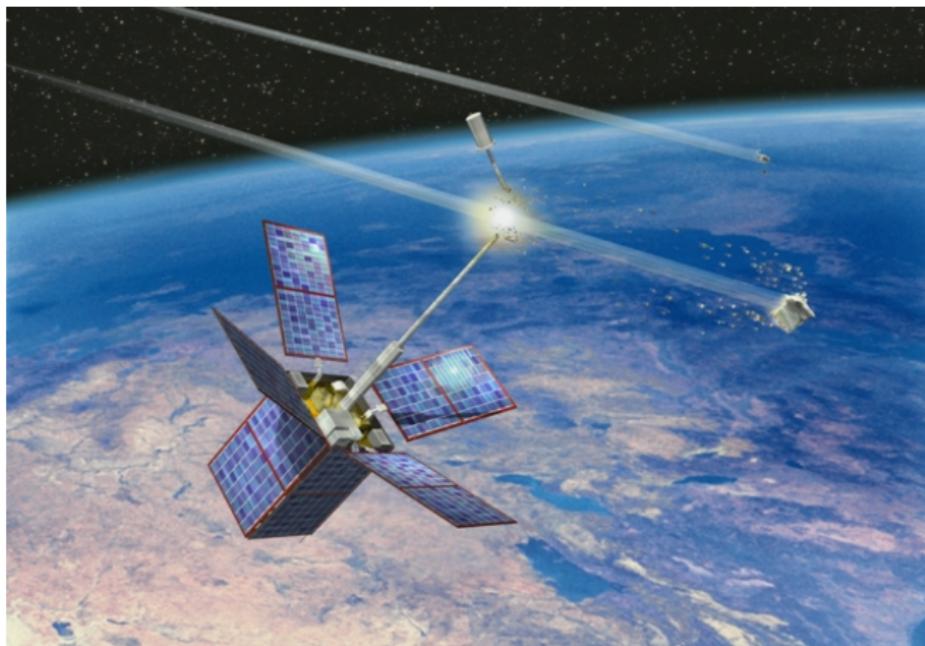


Figure: Cerise hit by a debris in 1996 (source : CNES/D. Ducros)

On-orbit collision

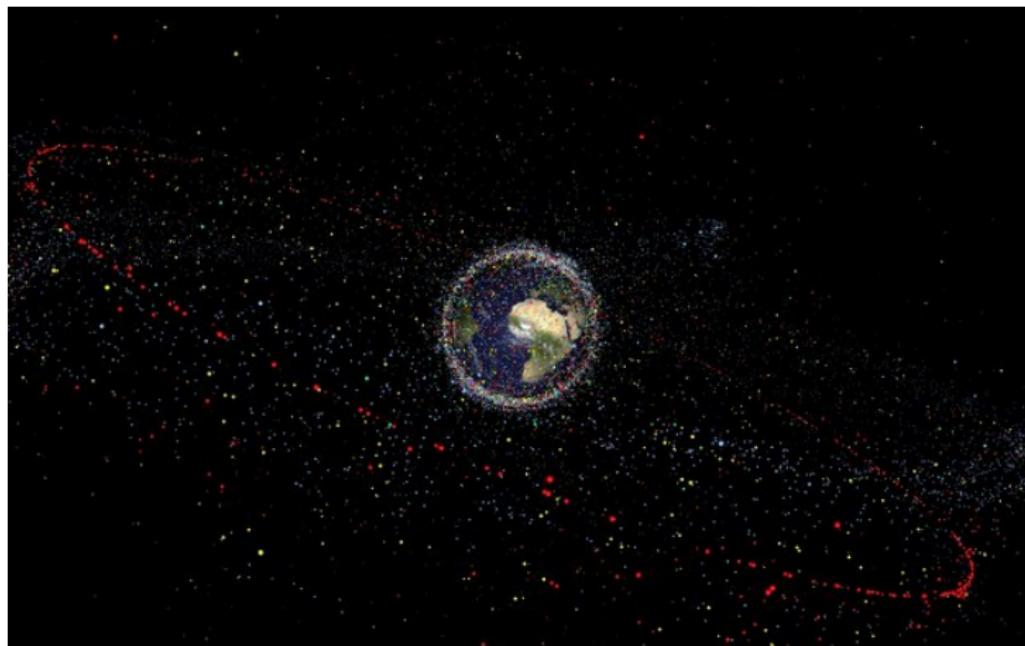


Figure: Space debris population model (source : ESA)

On-orbit collision

Context

- Two objects: primary P ([operational satellite](#)) and secondary S ([space debris](#))
- Information about their geometry, position, velocity at a given time
 - ~~~ [Affected by uncertainty](#)
- Needs:
 - Risk assessment
 - Design of a collision avoidance strategy
- ~~~ [compute the probability of collision](#)

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Classical assumptions

- Spherical objects
- Gaussian probability density functions
- Independent probability distribution laws

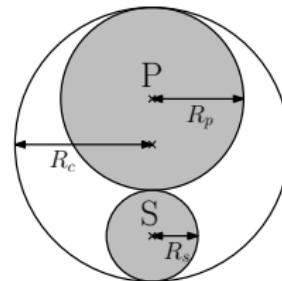


Figure: Combined spherical object

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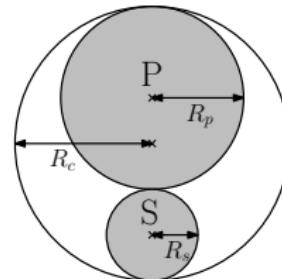


Figure: Combined spherical object

Probability of collision

Generally: 12-dimensional, Gaussian integrand, Complex integration domain

Computation: Monte-Carlo trials and/or simplified models

Short-term encounter model and probability of collision

- Framework: High relative velocity
 - Assumptions:
 - Rectilinear relative motion
 - No velocity uncertainty
 - Infinite encounter time horizon
- ~~ Probability of collision:
2-D integral over a disk.

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Formula

$$\mathcal{P} = \frac{1}{2\pi\sigma_x\sigma_y} \int_{\mathcal{B}((0,0), R)} \exp\left(-\frac{(x - \textcolor{brown}{x}_m)^2}{2\sigma_x^2} - \frac{(y - \textcolor{brown}{y}_m)^2}{2\sigma_y^2}\right) dx dy,$$

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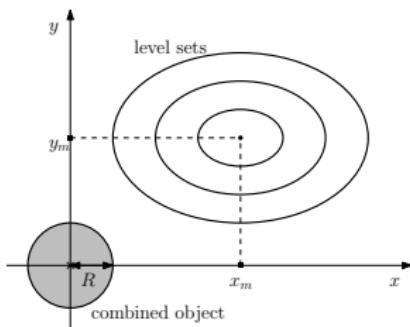


Figure: 2-D Gaussian integral over a disk

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where

- R : radius of combined object
- x_m, y_m : mean relative coordinates
- σ_x, σ_y : standard deviations of relative coordinates

Existing methods

- Methods based on numerical integration schemes:
Foster '92, Patera '01, Alfano '05.
- Analytic methods: Chan '97 \rightsquigarrow uses some simplifying assumptions ($\sigma_x = \sigma_y$)

Pro's and Con's

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- Analytic methods: Chan '97 ↪ uses some simplifying assumptions ($\sigma_x = \sigma_y$)
↪ provides truncation error bounds

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- Fast and already used in practice

Our purpose

Give a "simple", "analytic" formula, suitable for double-precision evaluation
and effective error bounds.

Our method - Underlying techniques

① Laplace transform:

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# Our method - Underlying techniques

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## ② D-finite functions

~~ solution of linear differential equation with polynomial coefficients

~~ power series coefficients satisfy a linear recurrence relation with polynomial coefficients

Example:

$$f(x) = \exp(x) \leftrightarrow \{f' - f = 0, f(0) = 1\} \leftrightarrow \{(n+1)f_{n+1} = f_n, f_0 = 1\}$$

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## ③ Finite-precision evaluation of power series prone to cancellation

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## Sketch of the proof - Laplace Transform

$\forall z \in \mathbb{R}^+$  :

$$g(z) := \mathcal{P}(\sqrt{z}) = \frac{1}{2\pi\sigma_x\sigma_y} \int_{\mathcal{B}((0,0),\sqrt{z})} \exp\left(-\frac{(x - \textcolor{brown}{x}_m)^2}{2\sigma_x^2} - \frac{(y - \textcolor{brown}{y}_m)^2}{2\sigma_y^2}\right) dx dy, \quad (1)$$

(3)

## Sketch of the proof - Laplace Transform

$\forall z \in \mathbb{R}^+$  :

$$g(\textcolor{violet}{z}) := \mathcal{P}(\sqrt{z}) = \frac{1}{2\pi\sigma_x\sigma_y} \int_{\mathcal{B}((0,0),\sqrt{z})} \exp\left(-\frac{(x-\textcolor{brown}{x}_m)^2}{2\sigma_x^2} - \frac{(y-\textcolor{brown}{y}_m)^2}{2\sigma_y^2}\right) dx dy, \quad (1)$$

$$\mathcal{L}(g)(\textcolor{blue}{t}) = \int_0^{+\infty} g(\textcolor{violet}{z}) \exp(-\textcolor{blue}{t}z) dz \quad (2)$$

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$$\dots = \frac{\exp\left(-\frac{\sigma_x^2 \mathbf{y}_m^2 + \sigma_y^2 \mathbf{x}_m^2}{2\sigma_x^2 \sigma_y^2} + \frac{\mathbf{y}_m^2}{2\sigma_y^2(2t\sigma_y^2 + 1)} + \frac{\mathbf{x}_m^2}{2\sigma_x^2(2t\sigma_x^2 + 1)}\right)}{t \sqrt{(2t\sigma_x^2 + 1)(2t\sigma_y^2 + 1)}} \quad (3)$$

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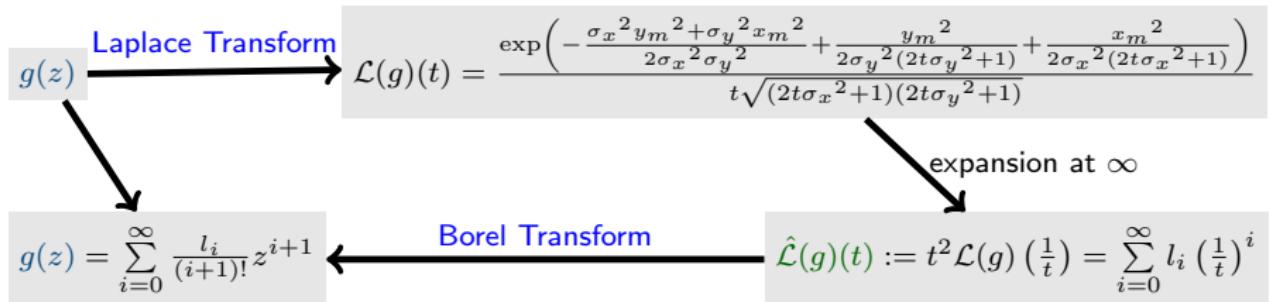
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$\mathcal{L}(g)$  is D-finite !

## Sketch of the proof - Borel-Laplace



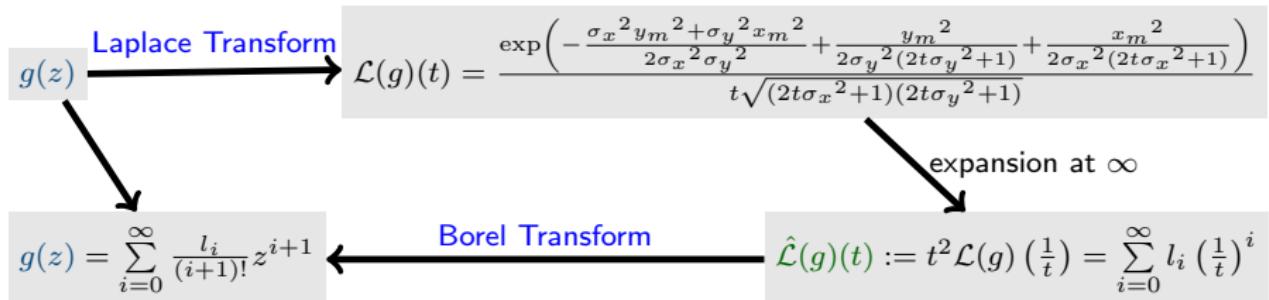
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- type  $\sigma = \frac{1}{2\sigma_y^2}$

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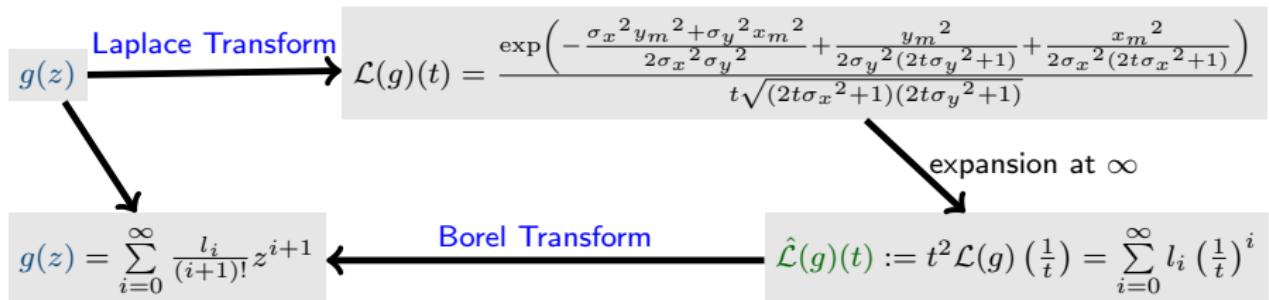
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 $\rightsquigarrow$  Compute everything with gfun

## Sketch of the proof - Borel-Laplace



$g(z)$  is:

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- sum prone to cancellation

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# Cancellation in finite precision power series evaluation

Example:  $\sigma_x = 115, \sigma_y = 1.41, x_m = 0.15, y_m = 3.88, \sqrt{z} = 15$

$$g(z) = \sum_{i=0}^{\infty} \frac{l_i}{(i+1)!} z^{i+1}$$

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$$g(225) = 0.16 \cdot 10^{-1} + 1.5 + 16.1 - 250 \dots + 2.2 \cdot 10^{19} - 2.6 \cdot 10^{19} - \dots + 4.3 - 0.14 - 0.60 \dots$$

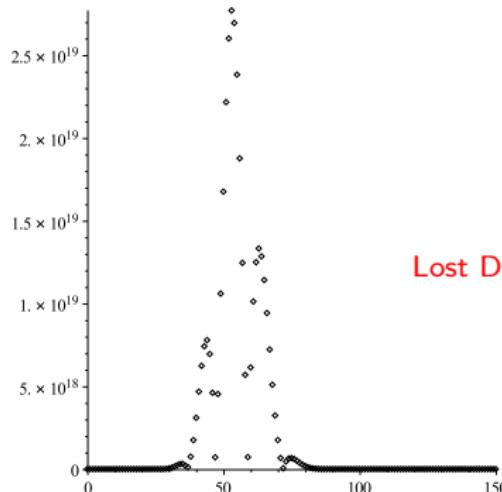
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Values of  $\left| \frac{l_i 225^{i+1}}{(i+1)!} \right|$ , compared to  $g(225) \simeq 0.1004$ :



$$\text{Lost Digits: } d_g(z) \simeq \log \frac{\max_i |g_i z^i|}{|g(z)|}$$

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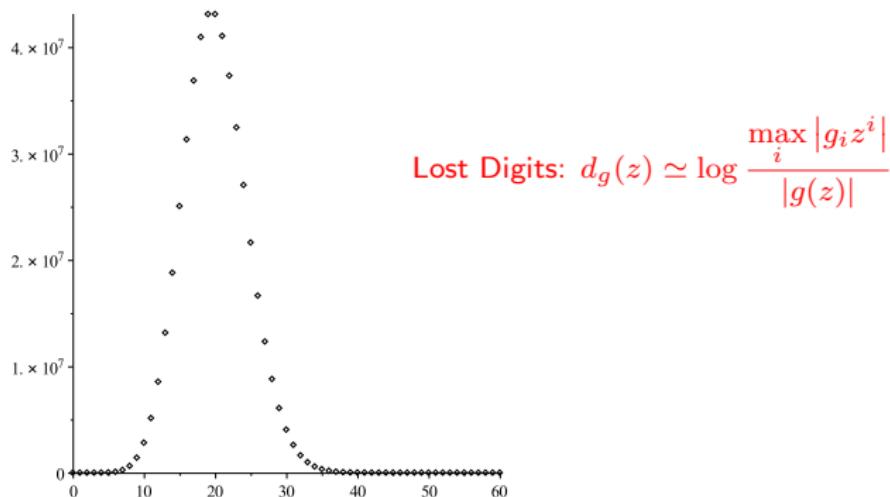
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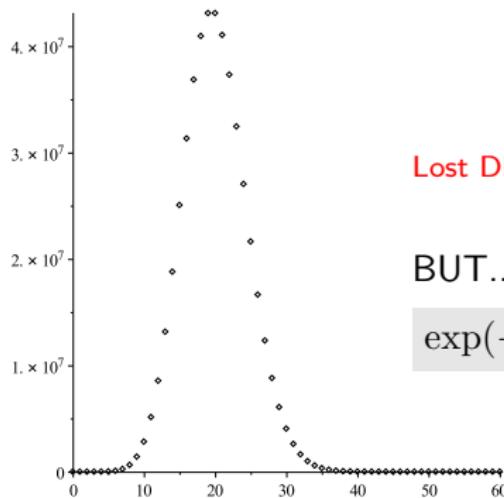


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BUT...

$$\exp(-x) = \frac{1}{\exp(x)}$$

No cancellation!

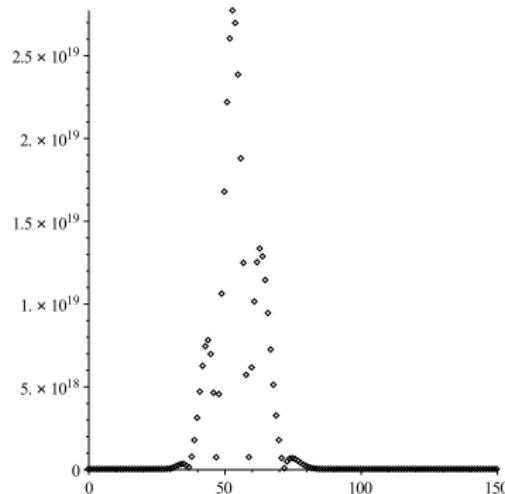
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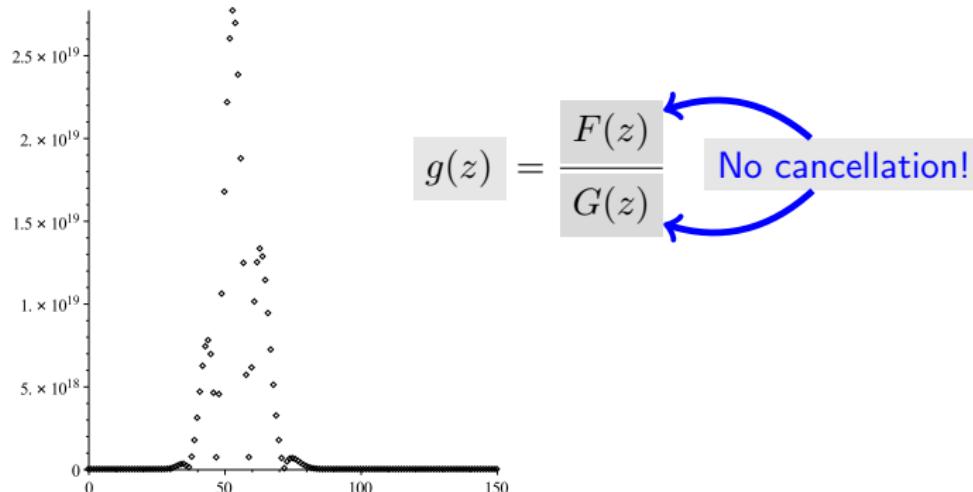
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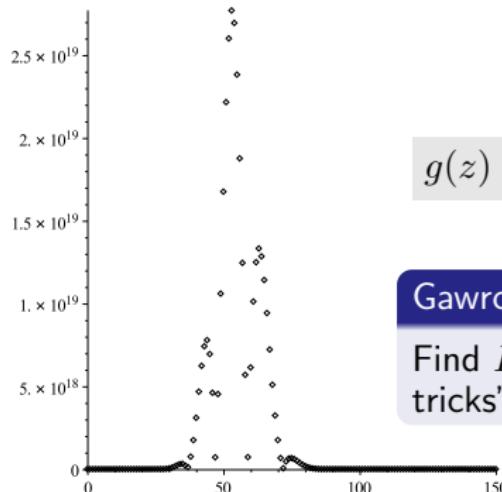
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$$g(z) = \frac{F(z)}{G(z)}$$

No cancellation!

Gawronski, Müller, Reinhard (2007) Method:

Find  $F(z)$  and  $G(z)$  using "complex analysis tricks"  $\rightsquigarrow$  indicator function.

## Sketch of the proof - Borel-Laplace + GMR Method

$$g(z) = \frac{F(z)}{G(z)} \xrightarrow{\text{Laplace}} \mathcal{L}(g)(t) = \frac{\exp\left(-\frac{\sigma_x^2 y_m^2 + \sigma_y^2 x_m^2}{2\sigma_x^2 \sigma_y^2} + \frac{y_m^2}{2\sigma_y^2(2t\sigma_y^2+1)} + \frac{x_m^2}{2\sigma_x^2(2t\sigma_x^2+1)}\right)}{t\sqrt{(2t\sigma_x^2+1)(2t\sigma_y^2+1)}}$$
$$g(z) = \sum_{i=0}^{\infty} \frac{l_i}{(i+1)!} z^{i+1} \xleftarrow{\text{Borel Transform}} \hat{\mathcal{L}}(g)(t) := t^2 \mathcal{L}(g)\left(\frac{1}{t}\right) = \sum_{i=0}^{\infty} l_i \left(\frac{1}{t}\right)^i$$

$g(z)$  is:

- D-finite
- entire function of exponential type
- type  $\sigma = \frac{1}{2\sigma_y^2}$

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- indicator function:  
 $|g(re^{i\theta})| \sim \exp(h(\theta)r)$  for large  $r$

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$$h(\theta) = \begin{cases} \frac{-\cos \theta}{2\sigma_y^2} & \text{if } \theta \in [\frac{\pi}{2}, \frac{3\pi}{2}] \\ 0 & \text{if } \theta \in [0, \frac{\pi}{2}) \cup (\frac{3\pi}{2}, 2\pi]. \end{cases}$$

## Zoom on Indicator functions

$$g(z) = \frac{F(z)}{G(z)}$$

- $|g(re^{i\theta})| \sim \exp(h(\theta)r)$  for large  $r$
- indicator of  $g$ :

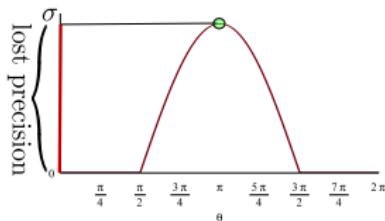
$$h(\theta) = \begin{cases} \frac{-\cos \theta}{2\sigma_y^2} & \text{if } \theta \in [\frac{\pi}{2}, \frac{3\pi}{2}] \\ 0 & \text{otherwise.} \end{cases}$$

## Zoom on Indicator functions

$$g(z) = \frac{F(z)}{G(z)}$$

- $|g(re^{i\theta})| \sim \exp(h(\theta)r)$  for large  $r$
- indicator of  $g$ :

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$$\text{lost precision} \sim |\sigma - h(0)|$$

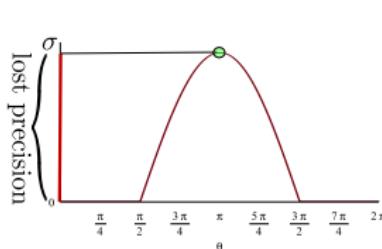
## Zoom on Indicator functions

$$g(z) = \frac{F(z)}{G(z)}$$

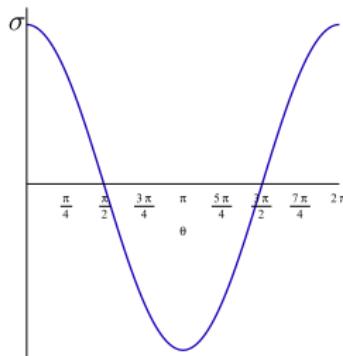
- $|g(re^{i\theta})| \sim \exp(h(\theta)r)$  for large  $r$
- indicator of  $g$ :

$$h(\theta) = \begin{cases} \frac{-\cos \theta}{2\sigma_y^2} & \text{if } \theta \in [\frac{\pi}{2}, \frac{3\pi}{2}] \\ 0 & \text{otherwise.} \end{cases}$$

- $G(z) = \exp(\sigma z)$   
indicator of  $G$ :



$$\text{lost precision} \sim |\sigma - h(0)|$$

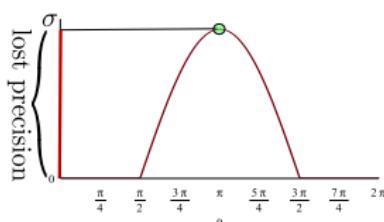


## Zoom on Indicator functions

$$G(z)g(z) = F(z)$$

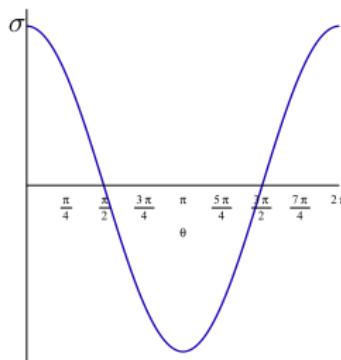
- $|g(re^{i\theta})| \sim \exp(h(\theta)r)$  for large  $r$
- indicator of  $g$ :

$$h(\theta) = \begin{cases} \frac{-\cos \theta}{2\sigma_y^2} & \text{if } \theta \in [\frac{\pi}{2}, \frac{3\pi}{2}] \\ 0 & \text{otherwise.} \end{cases}$$

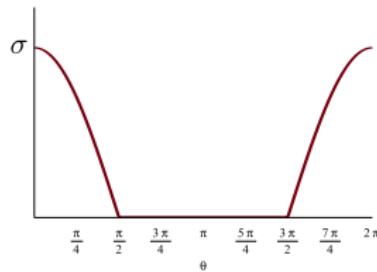


$$\text{lost precision} \sim |\sigma - h(0)|$$

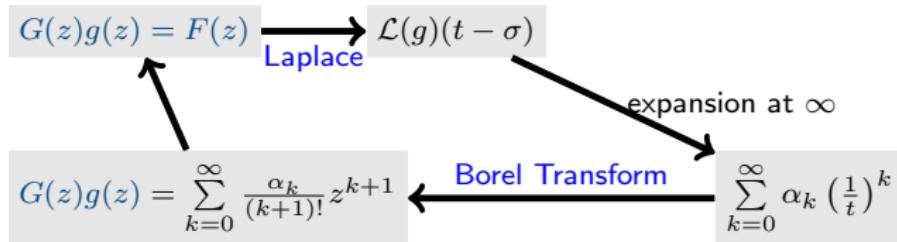
- $G(z) = \exp(\sigma z)$   
indicator of  $G$ :



- indicator of  $F$ :

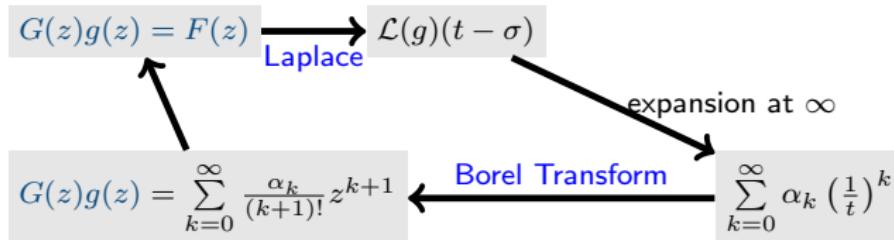


## Sketch of the proof - Borel-Laplace + GMR Method



- $G(z) = \exp(\sigma z)$
- $F$  is D-finite
- reduced cancellation for evaluating  $F, G$  on positive real line
- recurrence for  $\alpha_k$ :

## Sketch of the proof - Borel-Laplace + GMR Method



- $G(z) = \exp(\sigma z)$
- $F$  is D-finite
- reduced cancellation for evaluating  $F, G$  on positive real line
- recurrence for  $\alpha_k$ :

$$\begin{aligned} & - (32k\sigma_x^4\sigma_y^{10} + 128\sigma_x^4\sigma_y^{10})\alpha_{k+4} = (\sigma_x^4y_m^2 - 2\sigma_x^2\sigma_y^2y_m^2 + \sigma_y^4y_m^2)\alpha_k \\ & + ((-4\sigma_x^4\sigma_y^4 + 8\sigma_x^2\sigma_y^6 - 4\sigma_y^8)k - 10\sigma_x^4\sigma_y^4 - 6\sigma_x^4\sigma_y^2y_m^2 + 20\sigma_x^2\sigma_y^6y_m^2 + 8\sigma_x^2\sigma_y^4y_m^2 - 10\sigma_y^8 - 2\sigma_y^6y_m^2)\alpha_{k+1} \\ & + ((24\sigma_x^4\sigma_y^6 - 32\sigma_x^2\sigma_y^8 + 8\sigma_y^{10})k + 72\sigma_x^4\sigma_y^6 + 12\sigma_x^4\sigma_y^4y_m^2 - 92\sigma_x^2\sigma_y^8 - 8\sigma_x^2\sigma_y^6y_m^2 + 20\sigma_y^{10} + 4\sigma_y^8x_m^2)\alpha_{k+2} \\ & + ((-48\sigma_x^4\sigma_y^8 + 32\sigma_x^2\sigma_y^{10})k - 168\sigma_x^4\sigma_y^8 - 8\sigma_x^4\sigma_y^6y_m^2 + 104\sigma_x^2\sigma_y^{10} - 8\sigma_y^{10}x_m^2)\alpha_{k+3}, \end{aligned}$$

Prop. Coefficients  $\alpha_k$  are positive

Suppose  $\sigma_x > \sigma_y$ .

$\hat{L}(x) = \sum_{k=0}^{\infty} \alpha_k x^k$  satisfies  $\hat{L}'(x) = F(x)\hat{L}(x)$ ,  $\hat{L}(0) = \frac{\exp\left(-\frac{\sigma_x^2 y_m^2 + \sigma_y^2 x_m^2}{2\sigma_x^2 \sigma_y^2}\right)}{2\sigma_x \sigma_y}$ , where

$$\begin{aligned} F(x) = & \frac{y_m^2}{4\sigma_y^4} + \frac{\sigma_y^4 x_m^2}{(x(\sigma_x^2 - \sigma_y^2) - 2\sigma_x^2 \sigma_y^2)^2} - \frac{1}{-2\sigma_y^2 + x} \\ & + \frac{-\sigma_x^2 + \sigma_y^2}{2x(\sigma_x^2 - \sigma_y^2) - 4\sigma_x^2 \sigma_y^2}. \end{aligned}$$

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$$f_k = \frac{1 + \frac{\left(1 - \frac{\sigma_y^2}{\sigma_x^2}\right)^k \left((k+1) \left(\frac{x_m^2 \sigma_y^2}{\sigma_x^4}\right) + 1 - \frac{\sigma_y^2}{\sigma_x^2}\right)}{(2\sigma_y^2)^{k+1}}}{+ \begin{cases} 0, & k > 0 \\ \frac{y_m^2}{4\sigma_y^4}, & k = 0, \end{cases}}$$

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$$0 \leq f_k = \frac{1 + \frac{\left(1 - \frac{\sigma_y^2}{\sigma_x^2}\right)^k \left((k+1) \left(\frac{x_m^2 \sigma_y^2}{\sigma_x^4}\right) + 1 - \frac{\sigma_y^2}{\sigma_x^2}\right)}{(2\sigma_y^2)^{k+1}}}{+ \begin{cases} 0, & k > 0 \\ \frac{y_m^2}{4\sigma_y^4}, & k = 0, \end{cases}}$$

## Prop. Coefficients $\alpha_k$ are positive

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$\hat{L}(x) = \sum_{k=0}^{\infty} \alpha_k x^k$  satisfies  $\hat{L}'(x) = F(x)\hat{L}(x)$ ,  $\hat{L}(0) = \frac{\exp\left(-\frac{\sigma_x^2 y_m^2 + \sigma_y^2 x_m^2}{2\sigma_x^2 \sigma_y^2}\right)}{2\sigma_x \sigma_y}$ , where

$$F(x) = \frac{y_m^2}{4\sigma_y^4} + \frac{\sigma_y^4 x_m^2}{(x(\sigma_x^2 - \sigma_y^2) - 2\sigma_x^2 \sigma_y^2)^2} - \frac{1}{-2\sigma_y^2 + x} + \frac{-\sigma_x^2 + \sigma_y^2}{2x(\sigma_x^2 - \sigma_y^2) - 4\sigma_x^2 \sigma_y^2}.$$

$$0 \leq f_k = \frac{1 + \frac{\left(1 - \frac{\sigma_y^2}{\sigma_x^2}\right)^k \left((k+1) \left(\frac{x_m^2 \sigma_y^2}{\sigma_x^4}\right) + 1 - \frac{\sigma_y^2}{\sigma_x^2}\right)}{2}}{(2\sigma_y^2)^{k+1}} + \begin{cases} 0, & k > 0 \\ \frac{y_m^2}{4\sigma_y^4}, & k = 0, \end{cases}$$

$$0 \leq (n+1)\alpha_{n+1} = \sum_{i=0}^n f_i \cdot \alpha_{n-i}, \rightsquigarrow \text{by induction.}$$

## Bounds using majorant series

$$\text{Let } \gamma := \frac{1 + \frac{1}{2} \left( 1 - \frac{\sigma_y^2}{\sigma_x^2} + \frac{x_m^2 \sigma_y^2}{\sigma_x^4} + \frac{y_m^2}{\sigma_y^2} \right)}{2\sigma_y^2}, \bar{\alpha}_k := \alpha_0 \gamma^k \text{ and } \underline{\alpha}_k := \alpha_0 \left( \frac{1}{2\sigma_y^2} \right)^k.$$

Then  $\underline{\alpha}_k \leq \alpha_k \leq \bar{\alpha}_k, \forall k \in \mathbb{N}$ .

# Bounds using majorant series

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Then  $\underline{\alpha}_k \leq \alpha_k \leq \bar{\alpha}_k, \forall k \in \mathbb{N}$ .

Let  $\tilde{P}_N(z) := \sum_{k=0}^{N-1} \frac{\alpha_k z^k}{(k+1)!}$ . Then we have the following error bounds:

$\underline{\varepsilon}_N(z) \leq g(z) - \tilde{P}_N(z) \leq \bar{\varepsilon}_N(z)$ , where

$$\underline{\varepsilon}_N(z) := 2\alpha_0 \sigma_y^2 e^{-\frac{z}{2\sigma_y^2}} \frac{\left(\frac{z}{2\sigma_y^2}\right)^{N+1}}{(N+1)!},$$

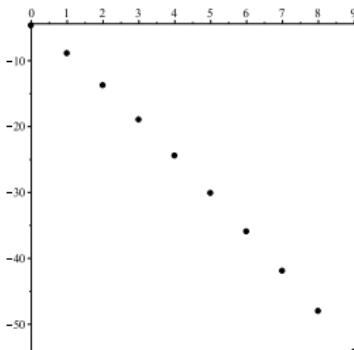
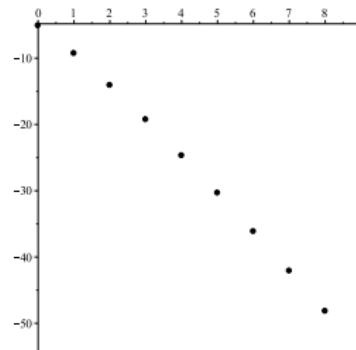
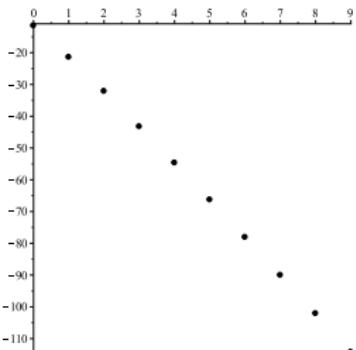
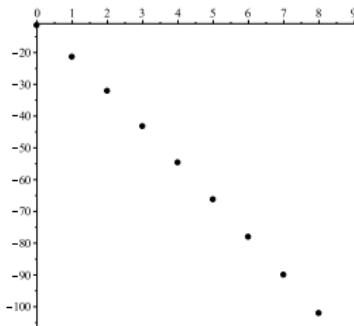
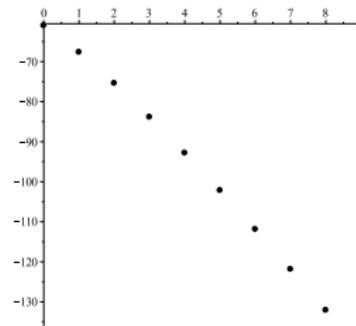
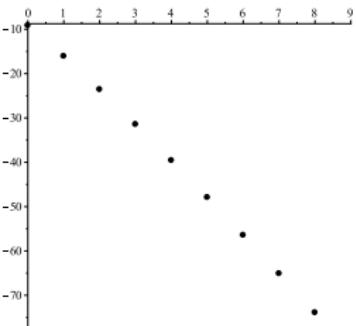
$$\bar{\varepsilon}_N(z) := \frac{\alpha_0}{\gamma} e^{-\frac{z}{2\sigma_y^2}} \frac{(z\gamma)^{N+1}}{N+1!}.$$

# Examples

## Sample 1

| Case # | Input parameters (km) |            |       |       |       |
|--------|-----------------------|------------|-------|-------|-------|
|        | $\sigma_x$            | $\sigma_y$ | $R$   | $x_m$ | $y_m$ |
| 1      | 0.05                  | 0.025      | 0.005 | 0.01  | 0     |
| 2      | 0.05                  | 0.025      | 0.005 | 0     | 0.01  |
| 3      | 0.075                 | 0.025      | 0.005 | 0.01  | 0     |
| 4      | 0.075                 | 0.025      | 0.005 | 0     | 0.01  |
| 5      | 3                     | 1          | 0.01  | 1     | 0     |
| 6      | 3                     | 1          | 0.01  | 0     | 1     |
| 7      | 3                     | 1          | 0.01  | 10    | 0     |
| 8      | 3                     | 1          | 0.01  | 0     | 10    |
| 9      | 10                    | 1          | 0.01  | 10    | 0     |
| 10     | 10                    | 1          | 0.01  | 0     | 10    |
| 11     | 3                     | 1          | 0.05  | 5     | 0     |
| 12     | 3                     | 1          | 0.05  | 0     | 5     |

Examples: quality  $\eta = \frac{\bar{\varepsilon}_{10}(z) - \underline{\varepsilon}_{10}(z)}{\underline{\varepsilon}_{10}(z) + \tilde{P}_{10}(z)}$  and plot  $\log(\tilde{p}_i z^i)$

Case 1:  $\eta = 23$ Case 2:  $\eta = 22$ Case 4:  $\eta = 22$ Case 6:  $\eta = 47$ Case 8:  $\eta = 33$ Case 11:  $\eta = 34$ 

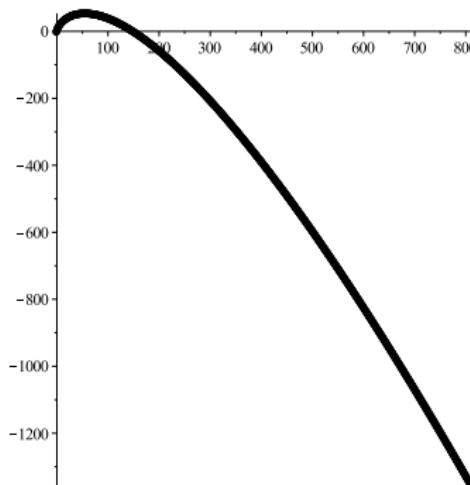
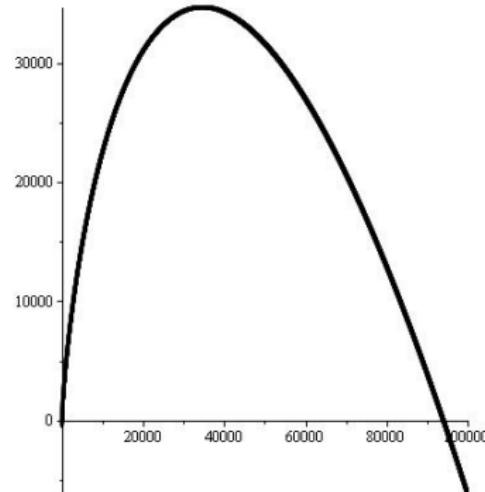
# Numerical study

Sample 1

| Case # | Probability of Collision (-) |                         |                         |                         |
|--------|------------------------------|-------------------------|-------------------------|-------------------------|
|        | Alfano                       | Patera                  | Chan                    | New method              |
| 1      | $9.742 \times 10^{-3}$       | $9.741 \times 10^{-3}$  | $9.754 \times 10^{-3}$  | $9.742 \times 10^{-3}$  |
| 2      | $9.181 \times 10^{-3}$       | $9.181 \times 10^{-3}$  | $9.189 \times 10^{-3}$  | $9.181 \times 10^{-3}$  |
| 3      | $6.571 \times 10^{-3}$       | $6.571 \times 10^{-3}$  | $6.586 \times 10^{-3}$  | $6.571 \times 10^{-3}$  |
| 4      | $6.125 \times 10^{-3}$       | $6.125 \times 10^{-3}$  | $6.135 \times 10^{-3}$  | $6.125 \times 10^{-3}$  |
| 5      | $1.577 \times 10^{-5}$       | $1.577 \times 10^{-5}$  | $1.577 \times 10^{-5}$  | $1.577 \times 10^{-5}$  |
| 6      | $1.011 \times 10^{-5}$       | $1.011 \times 10^{-5}$  | $1.011 \times 10^{-5}$  | $1.011 \times 10^{-5}$  |
| 7      | $6.443 \times 10^{-8}$       | $6.443 \times 10^{-8}$  | $6.443 \times 10^{-8}$  | $6.443 \times 10^{-8}$  |
| 8      | 0                            | $3.219 \times 10^{-27}$ | $3.216 \times 10^{-27}$ | $3.219 \times 10^{-27}$ |
| 9      | $3.033 \times 10^{-6}$       | $3.033 \times 10^{-6}$  | $3.033 \times 10^{-6}$  | $3.033 \times 10^{-6}$  |
| 10     | 0                            | $9.656 \times 10^{-28}$ | $9.645 \times 10^{-28}$ | $9.656 \times 10^{-28}$ |
| 11     | $1.039 \times 10^{-4}$       | $1.039 \times 10^{-4}$  | $1.039 \times 10^{-4}$  | $1.039 \times 10^{-4}$  |
| 12     | $1.564 \times 10^{-9}$       | $1.564 \times 10^{-9}$  | $1.556 \times 10^{-9}$  | $1.564 \times 10^{-9}$  |

— equal to reference value (from [Chan 2008])

Examples: quality  $\eta_N = \frac{\bar{\varepsilon}_N(z) - \underline{\varepsilon}_N(z)}{\bar{\varepsilon}_N(z) + \tilde{P}_N(z)}$  and plot  $\log(\tilde{p}_i z^i)$

Case 3 Alfano:  $\eta_{800} = 30$ Case 5 Alfano:  $\eta_{121000} = 20$ 

Sample 2 (from [Alfano 2009])

| Case # | Input parameters (m) |            |     |       |       |
|--------|----------------------|------------|-----|-------|-------|
|        | $\sigma_x$           | $\sigma_y$ | $R$ | $x_m$ | $y_m$ |
| 3      | 114.25               | 1.41       | 15  | 0.15  | 3.88  |
| 5      | 177.8                | 0.038      | 10  | 2.12  | -1.22 |

# Examples

Sample 2 (from [Alfano 2009])

| Case # | Input parameters (m) |            |     |       |       |
|--------|----------------------|------------|-----|-------|-------|
|        | $\sigma_x$           | $\sigma_y$ | $R$ | $x_m$ | $y_m$ |
| 3      | 114.25               | 1.41       | 15  | 0.15  | 3.88  |
| 5      | 177.8                | 0.038      | 10  | 2.12  | -1.22 |

| Alfano's test case number | Probability of collision (-) |            |                |
|---------------------------|------------------------------|------------|----------------|
|                           | Alfano                       | New method | Reference (MC) |
| 3                         | 0.10038                      | 0.10038    | 0.10085        |
| 5                         | 0.044712                     | 0.045509   | 0.044499       |

# Conclusion

## New method

- Analytical formula
- Reduced cancellation evaluation
- Error bounds
- No simplifying assumption

## Current and future work

- Saddle-point method for "degenerate" cases
- Long-term 3D encounter model
- Extension to polygonal cross-sections
- Extensive testings and comparisons with existing methods