# Optimal ellipsoidal overapproximations for robust optimal control

Florian Messerer

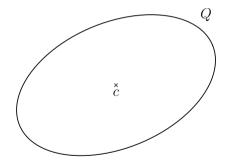
Systems Control and Optimization Laboratory, University of Freiburg

syscop group retreat Feb 15, 2023



▶ Define ellipsoid by center  $c \in \mathbb{R}^n$  and shape matrix  $Q \in \mathbb{S}_{++}^n$  (i.e.,  $Q \succ 0$ )

$$\mathcal{E}(Q,c) := \{ x \in \mathbb{R}^n \mid ||x - c||_{Q^{-1}} \le 1 \}$$

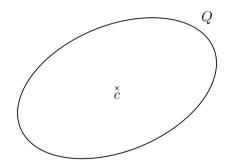




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- Denote by  $\lambda_i$ ,  $v_i$ , i = 1, ..., n, the eigenvalues / -vectors (normalized) of Q.
  - These correspond to the ellipsoid axes

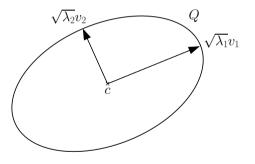




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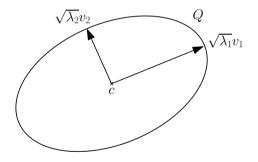


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- Denote by λ<sub>i</sub>, v<sub>i</sub>, i = 1,...,n, the eigenvalues / -vectors (normalized) of Q.
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- Measuring the size of an ellipsoid

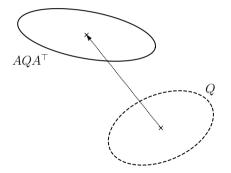
$$\operatorname{Tr} Q = \sum_{i=1}^n \lambda_i$$
 ("least squares") $\sqrt{\det Q} = \prod_{i=1}^n \sqrt{\lambda_i}$   $\propto$  Volume





#### Ellipsoid 101 – Affine transformation



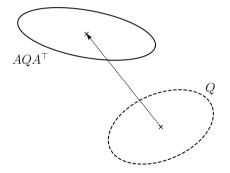


 $A \in \mathbb{R}^{m \times n}, \ b \in \mathbb{R}^{m},$  $A\mathcal{E}(Q, c) + b,$  $:= \{Ax + b \mid x \in \mathcal{E}(Q, c)\}$ 

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# Ellipsoid 101 – Affine transformation



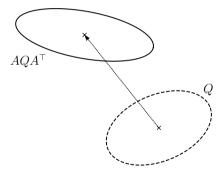


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$$= \mathcal{E}(AQA^{\top}, Ac + b)$$

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# Ellipsoid 101 – Affine transformation





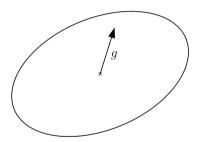
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center position of the ellipsoid usually unspectular  $\rightarrow$  We focus on ellipsoids centered around the origin

$$\mathcal{E}(Q):=\mathcal{E}(Q,0)$$

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# Support function



Any non-empty compact convex set S ⊂ ℝ<sup>n</sup> can be defined via its support function:

$$V(g) = \max_{x \in \mathbb{R}^n} g^\top x \quad \text{s.t.} \quad x \in \mathcal{S}$$

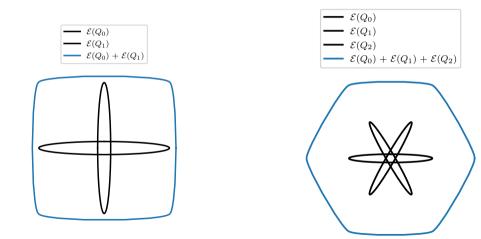
Important tool for analysis of convex setsFor ellipsoid:

$$V(g) = \max_{\substack{x \in \mathbb{R}^n \\ g^\top Qg}} g^\top x \quad \text{s.t.} \quad x \in \mathcal{E}(Q)$$
$$= \sqrt{g^\top Qg}$$

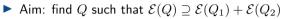


# Sum of ellipsoids (Minkowski sum)





Aim: find Q such that 
$$\mathcal{E}(Q) \supseteq \mathcal{E}(Q_1) + \mathcal{E}(Q_2)$$



• More general: Find Q such that  $\mathcal{E}(Q) \supseteq \sum_{k=1}^{N} \mathcal{E}(Q_k)$ 

- Aim: find Q such that  $\mathcal{E}(Q) \supseteq \mathcal{E}(Q_1) + \mathcal{E}(Q_2)$
- More general: Find Q such that  $\mathcal{E}(Q) \supseteq \sum_{k=1}^{N} \mathcal{E}(Q_k)$

• Construct family of outer approximations parametrized by  $\alpha \in \mathbb{R}_{++}^{KN}$ 

$$Q(\alpha) = \sum_{k=1}^{N} \frac{1}{\alpha_k} Q_k \quad \Rightarrow \quad \mathcal{E}(Q(\alpha)) \supseteq \sum_{k=1}^{N} \mathcal{E}(Q_k) \quad \forall \alpha \in \mathbb{R}_{++}^N \quad \text{with} \quad \sum_{k=1}^{N} \alpha_k = 1$$

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- Denote set of feasible  $\alpha$  by  $\mathcal{A}^N$  (basically a simplex)
- Parametrized outer approximation is tight (but not complete)

$$\bigcap_{\alpha \in \mathcal{A}^N} \mathcal{E}(Q(\alpha)) = \sum_{k=1}^N \mathcal{E}(Q_k)$$

• In general: Choose  $\alpha$  according to some criterion

• e.g., such that  $\mathcal{E}(Q(\alpha))$  has minimal size, e.g.,  $\min_{\alpha \in \mathcal{A}^N} \operatorname{Tr}(Q(\alpha))$ • or  $\mathcal{E}(Q(\alpha))$  tight in a given direction  $g \in \mathbb{R}^n$  (approximation touches true sum)

$$\min_{\alpha \in \mathcal{A}^N} \left( \max_{x \in \mathbb{R}^n} g^\top x \quad \text{s.t.} \quad x \in \mathcal{E}(Q(\alpha)) \right) = \min_{\alpha \in \mathcal{A}^N} \sqrt{g^\top Q(\alpha)g} \quad \hat{=} \min_{\alpha \in \mathcal{A}^N} \operatorname{Tr}(gg^\top Q(\alpha))$$

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• Special case N = 2

$$\blacktriangleright \ Q(\alpha) = \frac{1}{\alpha_1}Q_1 + \frac{1}{\alpha_2}Q_2 \text{ with } \alpha_1 + \alpha_2 = 1$$

• Reparametrize:  $\alpha_2 = 1 - \alpha_1$ ,  $\beta = \frac{1}{1 - \alpha_1} > 0$ 

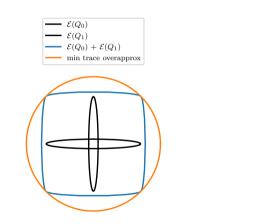
$$\hat{Q}(\beta) = (1 + \frac{1}{\beta})Q_1 + (1 + \beta)Q_2$$

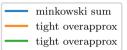
Inclusion-minimal (contains all the "best" overapproximations)

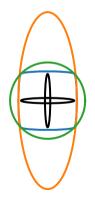
$$\arg\min_{\beta>0} \operatorname{Tr} \tilde{Q}(\beta) = \arg\min_{\beta>0} (1+\frac{1}{\beta}) \operatorname{Tr} Q_1 + (1+\beta) \operatorname{Tr} Q_2 = \sqrt{\frac{\operatorname{Tr} Q_1}{\operatorname{Tr} Q_2}}$$

# Overapproximations of sum of two ellipsoids

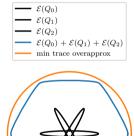


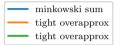


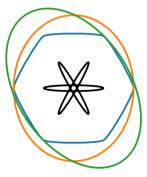




# Overapproximations of sum of three ellipsoids











$$x_{k+1} = Ax_k + \Gamma w_k$$

Reachable set

 $x_k \in \mathcal{E}(P_k), \ w_k \in \mathcal{E}(W)$  $\Rightarrow x_{k+1} \in \mathcal{E}(AP_k A^{\top}) + \mathcal{E}(\Gamma W \Gamma^{\top})$ 



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- Uncertainty set not ellipsoidal :(
- Overapproximate by ellipsoid



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Overapproximation of reachable set

$$x_k \in \mathcal{E}(P_k(\beta)), \ w_k \in \mathcal{E}(W)$$
$$P_{k+1}(\beta) = (1+\beta_k)AP_k(\beta)A^\top + (1+\frac{1}{\beta_k})\Gamma W\Gamma^\top$$
$$\Rightarrow x_{k+1} \in \mathcal{E}(P_{k+1}(\beta))$$



$$x_{k+1} = Ax_k + \Gamma w_k$$

Reachable set

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$$P_{k+1}(\beta) = (1+\beta_k)AP_k(\beta)A^\top + (1+\frac{1}{\beta_k})\Gamma W\Gamma^\top$$
$$\Rightarrow x_{k+1} \in \mathcal{E}(P_{k+1}(\beta))$$

# Overapproximation OCP



$$\begin{array}{ll}
\min_{\substack{\beta_0, \dots, \beta_{N-1} \in \mathbb{R}_{++}, \\ P_0, \dots, P_N}} & \sum_{k=0}^N \operatorname{Tr} L_k P_k \\ & \text{s.t.} & P_0 = \bar{P}_0, \\ & P_{k+1} = (1+\beta_k) A P_k A^\top + (1+\frac{1}{\beta_k}) \Gamma W \Gamma^\top, \quad k = 0, \dots, N. \end{array}$$
(1a)

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(1a)

Eliminating P<sub>k</sub> and substituting exp γ ← β results in convex problem
 special case A = I, L<sub>0</sub> = ··· = L<sub>N-1</sub> = 0 or A = I, L<sub>0</sub> = ··· = L<sub>N</sub>
 solve by forward recursion, β<sub>k</sub> = √ (Tr ΓWΓ<sup>T</sup>)/(Tr P<sub>k</sub>)
 Recursive overapproximation of N sums of two ellipsoids vs. overapproximation of one sum of N ellipsoids?

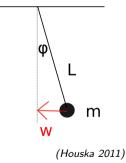
No loss of expressiveness (I think)

# Example – Linearized Pendulum

$$x = \begin{bmatrix} \varphi \\ \omega \end{bmatrix}, \quad \dot{x} = \begin{bmatrix} \omega \\ -\frac{g}{L}\varphi + \frac{1}{mL}w \end{bmatrix}$$

- discretize in time with T = 1.2, N = 10
- uncertainty  $w \in [-1,1]$  piecewise constant
- $\blacktriangleright \text{ Start at } x_0 = 0.$
- compute reachable set at final time and compare to overapproximations

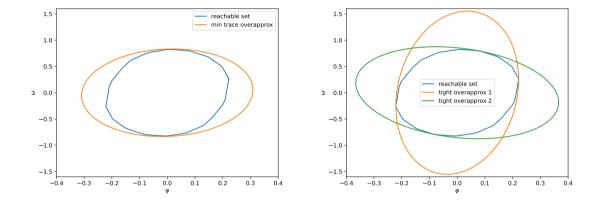
$$\min_{\beta > 0} \operatorname{Tr} P_N(\beta), \qquad \min_{\beta > 0} \operatorname{Tr}(gg^\top P_N(\beta)),$$





# Example – Linearized Pendulum





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Now consider controlled system

 $x_{k+1} = Ax_k + Bu_k + \Gamma w_k$ 

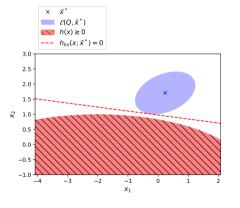
plan over feedback law to manipulate the ellipsoids

$$u_k = \bar{u}_k + K_k(x - \bar{x}_k)$$
$$P_{k+1} = (1 + \beta_k)(A + BK_k)P_k(A + BK_k)^\top + (1 + \frac{1}{\beta_k})\Gamma W \Gamma^\top$$

Linearize Constraints

$$h(x) \le 0 \quad \forall x \in \mathcal{E}(P, \bar{x})$$
  
$$\to \quad h(\bar{x}) + \nabla h(\bar{x})^{\top} (x - \bar{x}) \le 0 \quad \forall x \in \mathcal{E}(P, \bar{x})$$

 $\rightarrow$  Conservative for concave  $h(\boldsymbol{x})$ 





Robust OCP with optimal overapproximation and feedback, for linear dynamics, and "concave constraints".

$$\begin{array}{ll} \begin{array}{ll} \min_{x,u,\beta,P,K} & \sum_{k=0}^{N-1} l_k(\bar{x}_k,\bar{u}_k) + l_N(\bar{x}_N) \\ \text{s.t.} & \bar{x}_0 = \bar{x}_0, \ P_0 = \bar{P}_0, \\ & \bar{x}_{k+1} = A_k \bar{x}_k + B_k \bar{u}_k, & k = 0, \dots, N-1 \\ & P_{k+1} = (1+\beta_k)(A_k + B_k K_k) P_k(A_k + B_k K_k)^\top + (1+\frac{1}{\beta_k}) \tilde{W}_k^\top, & k = 0, \dots, N-1 \\ & 0 \ge h_k(\bar{x}_k,\bar{u}_k) + \nabla h_k(\bar{x}_k,\bar{u}_k)^\top (x-\bar{x}) & \forall z \in \mathcal{E}(P_z(P_k,K_k),\bar{z}), \ k = 0, \dots, N-1 \\ & 0 \ge h_N(\bar{x}_N) + \nabla h_N(\bar{x}_N)^\top (x-\bar{x}_N) & \forall x \in \mathcal{E}(P_N), \end{array}$$

with z = (x, u) and  $P_z$  the corresponding ellipsoid matrix

### Further considerations



- $\blacktriangleright\,$  Establish advantage of minimizing over  $\beta,\,K$ 
  - $\blacktriangleright$  vs. precomputing arbitrary LQR gain and choosing  $\beta$  as minimizing trace step-by-step
  - $\blacktriangleright$  feedback  $\rightarrow$  small uncertainty  $\rightarrow$  choice of  $\beta$  less relevant
- Design taylored algorithm, ZORO / SIRO style (alternate Riccati recursion, "Trace OCP", and nominal OCP with fixed back-off?)
- Find a nice linear system as example
- Alternative: affine-in-state-and-disturbance

 $x_{k+1} = A(u_k)x_k + \Gamma(u_k)w_k + b(u_k)$ 

- in this case without feedback-law
- Examples of this system class
  - systems with controlled mass-flow-rate (heating)