

# Lecture #4: Deployment via Geometric Optimization

Francesco Bullo<sup>1</sup> Jorge Cortés<sup>2</sup> Sonia Martínez<sup>2</sup>



<sup>1</sup>Department of Mechanical Engineering  
University of California, Santa Barbara  
[bullo@engineering.ucsb.edu](mailto:bullo@engineering.ucsb.edu)

<sup>2</sup>Mechanical and Aerospace Engineering  
University of California, San Diego  
[{cortes,soniamd}@ucsd.edu](mailto:{cortes,soniamd}@ucsd.edu)

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## Summary introduction



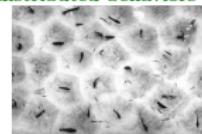
- Another motion coordination objective: deployment
- optimal task allocation and space partitioning, optimal placement and tuning of sensors
- Connection with geometric optimization and basic behaviors
- Formal definition and analysis of tasks and algorithms

## Coverage optimization

### DESIGN of performance metrics

- how to cover a region with  $n$  minimum-radius overlapping disks?
- how to design a minimum-distortion (fixed-rate) vector quantizer? (Lloyd '57)
- where to place mailboxes in a city / cache servers on the internet?

### ANALYSIS of cooperative distributed behaviors



Barlow, Hexagonal territories, Animal Behavior, 1974

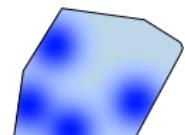
- how do animals share territory?  
what if every fish in a swarm goes toward center of own dominance region?
- what if each vehicle goes to center of mass of own Voronoi cell?
- what if each vehicle moves away from closest vehicle?

## Expected-value multicenter function

**Objective:** Given sensors/nodes/robots/sites ( $p_1, \dots, p_n$ ) moving in environment  $Q$  achieve **optimal coverage**

$$\phi : \mathbb{R}^d \rightarrow \mathbb{R}_{\geq 0} \text{ density}$$

$f : \mathbb{R}_{\geq 0} \rightarrow \mathbb{R}$  non-increasing and piecewise continuously differentiable, possibly with finite jump discontinuities



$$\text{maximize } \mathcal{H}_{\exp}(p_1, \dots, p_n) = E_{\phi} \left[ \max_{i \in \{1, \dots, n\}} f(\|q - p_i\|) \right]$$

## $\mathcal{H}_{\text{exp}}$ -optimality of the Voronoi partition

Alternative expression in terms of Voronoi partition,

$$\mathcal{H}_{\text{exp}}(p_1, \dots, p_n) = \sum_{i=1}^n \int_{V_i(\mathcal{P})} f(\|q - p_i\|_2) \phi(q) dq$$

for  $(p_1, \dots, p_n)$  distinct

### Proposition

Let  $\mathcal{P} = \{p_1, \dots, p_n\} \in \mathbb{F}(S)$ . For any performance function  $f$  and for any partition  $\{W_1, \dots, W_n\} \subset \mathbb{P}(S)$  of  $S$ ,

$$\mathcal{H}_{\text{exp}}(p_1, \dots, p_n, V_1(\mathcal{P}), \dots, V_n(\mathcal{P})) \geq \mathcal{H}_{\text{exp}}(p_1, \dots, p_n, W_1, \dots, W_n),$$

and the inequality is strict if any set in  $\{W_1, \dots, W_n\}$  differs from the corresponding set in  $\{V_1(\mathcal{P}), \dots, V_n(\mathcal{P})\}$  by a set of positive measure

## Distortion problem

$$f(x) = -x^2$$

$$\mathcal{H}_{\text{distor}}(p_1, \dots, p_n) = - \sum_{i=1}^n \int_{V_i(\mathcal{P})} \|q - p_i\|_2^2 \phi(q) dq = - \sum_{i=1}^n J_\phi(V_i(\mathcal{P}), p_i)$$

( $J_\phi(W, p)$  is moment of inertia). Note

$$\begin{aligned} \mathcal{H}_{\text{distor}}(p_1, \dots, p_n, W_1, \dots, W_n) \\ = - \sum_{i=1}^n J_\phi(W_i, CM_\phi(W_i)) - \sum_{i=1}^n A_\phi(W_i) \|p_i - CM_\phi(W_i)\|^2 \end{aligned}$$

### Proposition

Let  $\{W_1, \dots, W_n\} \subset \mathbb{P}(S)$  be a partition of  $S$ . Then,

$$\begin{aligned} \mathcal{H}_{\text{distor}}(CM_\phi(W_1), \dots, CM_\phi(W_n), W_1, \dots, W_n) \\ \geq \mathcal{H}_{\text{distor}}(p_1, \dots, p_n, W_1, \dots, W_n), \end{aligned}$$

and the inequality is strict if there exists  $i \in \{1, \dots, n\}$  for which  $W_i$  has non-vanishing area and  $p_i \neq CM_\phi(W_i)$

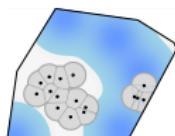
## Area problem

$$f(x) = 1_{[0,a]}(x), a \in \mathbb{R}_{>0}$$

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$$\begin{aligned} \mathcal{H}_{\text{area},a}(p_1, \dots, p_n) &= \sum_{i=1}^n \int_{V_i(\mathcal{P})} 1_{[0,a]}(\|q - p_i\|_2) \phi(q) dq \\ &= \sum_{i=1}^n \int_{V_i(\mathcal{P}) \cap \overline{B}(p_i, a)} \phi(q) dq \\ &= \sum_{i=1}^n A_\phi(V_i(\mathcal{P}) \cap \overline{B}(p_i, a)) = A_\phi(\bigcup_{i=1}^n \overline{B}(p_i, a)), \end{aligned}$$

Area, measured according to  $\phi$ , covered by the union of the  $n$  balls  $\overline{B}(p_1, a), \dots, \overline{B}(p_n, a)$



## Mixed distortion-area problem

$$f(x) = -x^2 1_{[0,a]}(x) + b 1_{[a,+\infty]}(x), \text{ with } a \in \mathbb{R}_{>0} \text{ and } b \leq -a^2$$

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$$\mathcal{H}_{\text{distor-area},a,b}(p_1, \dots, p_n) = - \sum_{i=1}^n J_\phi(V_{i,a}(\mathcal{P}), p_i) + b A_\phi(Q \setminus \bigcup_{i=1}^n \overline{B}(p_i, a)),$$

If  $b = -a^2$ , performance  $f$  is continuous, and we write  $\mathcal{H}_{\text{distor-area},a}$ .

Extension to sets of points and partitions reads

$$\begin{aligned} \mathcal{H}_{\text{distor-area},a}(p_1, \dots, p_n, W_1, \dots, W_n) \\ = - \sum_{i=1}^n \left( J_\phi(W_i \cap \overline{B}(p_i, a), p_i) + a^2 A_\phi(W_i \cap (S \setminus \overline{B}(p_i, a))) \right). \end{aligned}$$

### Proposition ( $\mathcal{H}_{\text{distor-area},a}$ -optimality of centroid locations)

Let  $\{W_1, \dots, W_n\} \subset \mathbb{P}(S)$  be a partition of  $S$ . Then,

$$\begin{aligned} \mathcal{H}_{\text{distor-area},a}(CM_\phi(W_1 \cap \overline{B}(p_1, a)), \dots, CM_\phi(W_n \cap \overline{B}(p_n, a)), W_1, \dots, W_n) \\ \geq \mathcal{H}_{\text{distor}}(p_1, \dots, p_n, W_1, \dots, W_n), \end{aligned}$$

and the inequality is strict if there exists  $i \in \{1, \dots, n\}$  for which  $W_i$  has non-vanishing area and  $p_i \neq CM_\phi(W_i \cap \overline{B}(p_i, a))$ .

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## Smoothness properties of $\mathcal{H}_{\text{exp}}$

$\text{Dscn}(f)$  (finite) discontinuities of  $f$   
 $f_-$  and  $f_+$ , limiting values from the left and from the right

### Theorem

Expected-value multicenter function  $\mathcal{H}_{\text{exp}} : S^n \rightarrow \mathbb{R}$  is

- 1 globally Lipschitz on  $S^n$ ; and
- 2 continuously differentiable on  $S^n \setminus \mathcal{S}_{\text{coinc}}$ , where

$$\begin{aligned} \frac{\partial \mathcal{H}_{\text{exp}}}{\partial p_i}(P) &= \int_{V_i(P)} \frac{\partial}{\partial p_i} f(\|q - p_i\|_2) \phi(q) dq \\ &+ \sum_{a \in \text{Dscn}(f)} (f_-(a) - f_+(a)) \int_{V_i(P) \cap \partial \overline{B}(p_i, a)} n_{\text{out}, \overline{B}(p_i, a)}(q) \phi(q) dq \\ &\quad = \text{integral over } V_i + \text{integral along arcs in } V_i \end{aligned}$$

Therefore, the gradient of  $\mathcal{H}_{\text{exp}}$  is spatially distributed over  $\mathcal{G}_D$

## Some proof ideas

Consider the case of smooth performance  $f$ ,

$$\begin{aligned} \frac{\partial \mathcal{H}_{\text{exp}}}{\partial p_i}(P) &= \int_{V_i(P)} \frac{\partial}{\partial p_i} f(\|q - p_i\|) \phi(q) dq \\ &+ \int_{\partial V_i(P)} f(\|q - p_i\|) \langle n_i(q), \frac{\partial q}{\partial p_i} \rangle \phi(q) dq \\ &+ \sum_j \text{neigh } i \int_{V_j(P) \cap V_i(P)} f(\|q - p_j\|) \langle n_{ji}(q), \frac{\partial q}{\partial p_i} \rangle \phi(q) dq \end{aligned}$$

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## Some proof ideas



$$\begin{aligned} \frac{\partial \mathcal{H}_{\text{exp}}}{\partial p_i}(P) &= \int_{V_i(P)} \frac{\partial}{\partial p_i} f(\|q - p_i\|) \phi(q) dq \underbrace{= 2 A_\phi(V_i(P)) (\text{CM}_\phi(V_i(P)) - p_i)}_{\text{for } f(x)=x^2} \\ &+ \int_{\partial V_i(P)} f(\|q - p_i\|) \langle n_i(q), \frac{\partial q}{\partial p_i} \rangle \phi(q) dq \\ &- \int_{\partial V_i(P)} f(\|q - p_i\|) \langle n_i(q), \frac{\partial q}{\partial p_i} \rangle \phi(q) dq \end{aligned}$$

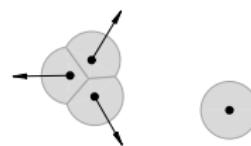
## Particular gradients

**Distortion problem:** continuous performance,

$$\frac{\partial \mathcal{H}_{\text{distor}}}{\partial p_i}(P) = 2 A_\phi(V_i(P)) (\text{CM}_\phi(V_i(P)) - p_i)$$

**Area problem:** performance has single discontinuity,

$$\frac{\partial \mathcal{H}_{\text{area}, a}}{\partial p_i}(P) = \int_{V_i(P) \cap \partial \overline{B}(p_i, a)} n_{\text{out}, \overline{B}(p_i, a)}(q) \phi(q) dq$$



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**Mixed distortion-area:** continuous performance ( $b = -a^2$ ),

$$\frac{\partial \mathcal{H}_{\text{distor-area}, a}}{\partial p_i}(P) = 2 A_\phi(V_{i,a}(P)) (\text{CM}_\phi(V_{i,a}(P)) - p_i)$$

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## Tuning the optimization problem

Gradients of  $\mathcal{H}_{\text{area},a}$ ,  $\mathcal{H}_{\text{distor-area},a,b}$  are distributed over  $\mathcal{G}_{\text{LD}}(2a)$

Robotic agents with range-limited interactions can compute gradients of  $\mathcal{H}_{\text{area},a}$  and  $\mathcal{H}_{\text{distor-area},a,b}$  as long as  $r \geq 2a$

### Proposition (Constant-factor approximation of $\mathcal{H}_{\text{distor}}$ )

Let  $S \subset \mathbb{R}^d$  be bounded and measurable. Consider the mixed distortion-area problem with  $a \in [0, \text{diam } S]$  and  $b = -\text{diam}(S)^2$ . Then, for all  $P \in S^n$ ,

$$\mathcal{H}_{\text{distor-area},a,b}(P) \leq \mathcal{H}_{\text{distor}}(P) \leq \beta^2 \mathcal{H}_{\text{distor-area},a,b}(P) < 0,$$

where  $\beta = \frac{a}{\text{diam}(S)} \in [0, 1]$

Similarly, constant-factor approximations of  $\mathcal{H}_{\text{exp}}$

## Geometric-center laws

Uniform networks  $\mathcal{S}_D$  and  $\mathcal{S}_{LD}$  of locally-connected first-order agents in a polytope  $Q \subset \mathbb{R}^d$  with the Delaunay and  $r$ -limited Delaunay graphs as communication graphs

All laws share similar structure

*At each communication round each agent performs the following tasks:*

- it transmits its position and receives its neighbors' positions;
- it computes a notion of geometric center of its own cell determined according to some notion of partition of the environment

*Between communication rounds, each robot moves toward this center*

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## VRN-CNTRD ALGORITHM

Optimizes distortion  $\mathcal{H}_{\text{distor}}$

Robotic Network:  $\mathcal{S}_D$  in  $Q$ , with absolute sensing of own position

Distributed Algorithm: VRN-CNTRD

Alphabet:  $A = \mathbb{R}^d \cup \{\text{null}\}$

function msg( $p, i$ )

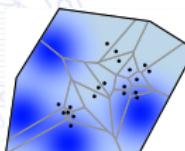
1: return  $p$

function ctl( $p, y$ )

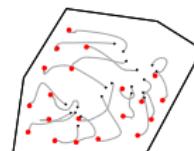
1:  $V := Q \cap (\bigcap \{H_{p,p_{\text{rcvd}}} \mid \text{for all non-null } p_{\text{rcvd}} \in y\})$

2: return  $\text{CM}_\phi(V) - p$

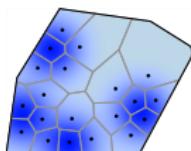
## Simulation



initial configuration



gradient descent



final configuration

For  $\varepsilon \in \mathbb{R}_{>0}$ , the  $\varepsilon$ -distortion deployment task

$$\mathcal{T}_{\varepsilon\text{-distor-dply}}(P) = \begin{cases} \text{true,} & \text{if } \|p^{[i]} - \text{CM}_\phi(V^{[i]}(P))\|_2 \leq \varepsilon, \quad i \in \{1, \dots, n\}, \\ \text{false,} & \text{otherwise,} \end{cases}$$

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# Voronoi-centroid law on planar vehicles

Robotic Network:  $\mathcal{S}_{\text{vehicles}}$  in  $Q$  with absolute sensing of own position

Distributed Algorithm: VRN-CNTRD-DYNMCS

Alphabet:  $A = \mathbb{R}^2 \cup \{\text{null}\}$

function msg( $(p, \theta), i$ )

1: return  $p$

function ctl( $(p, \theta), (p_{\text{smpid}}, \theta_{\text{smpid}}), y$ )

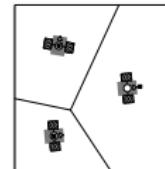
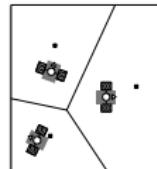
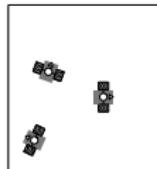
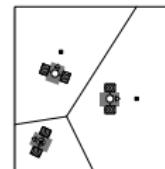
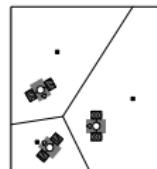
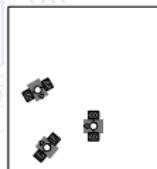
1:  $V := Q \cap (\bigcap \{H_{p_{\text{smpid}}, p_{\text{rcvd}}} \mid \text{for all non-null } p_{\text{rcvd}} \in y\})$

2:  $v := -k_{\text{prop}}(\cos \theta, \sin \theta) \cdot (p - \text{CM}_\phi(V))$

3:  $\omega := 2k_{\text{prop}} \arctan \frac{(-\sin \theta, \cos \theta) \cdot (p - \text{CM}_\phi(V))}{(\cos \theta, \sin \theta) \cdot (p - \text{CM}_\phi(V))}$

4: return  $(v, \omega)$

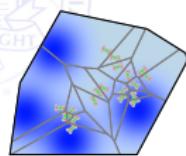
# Algorithm illustration



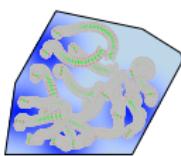
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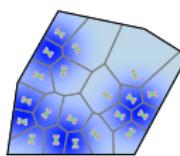
# Simulation



initial configuration



gradient descent



final configuration

# LMTD-VRN-NRML algorithm

Optimizes area  $\mathcal{H}_{\text{area}, \frac{r}{2}}$

Robotic Network:  $\mathcal{S}_{\text{LD}}$  in  $Q$  with absolute sensing of own position and with communication range  $r$

Distributed Algorithm: LMTD-VRN-NRML

Alphabet:  $A = \mathbb{R}^d \cup \{\text{null}\}$

function msg( $p, i$ )

1: return  $p$

function ctl( $p, y$ )

1:  $V := Q \cap (\bigcap \{H_{p, p_{\text{rcvd}}} \mid \text{for all non-null } p_{\text{rcvd}} \in y\})$

2:  $v := \int_{V \cap \partial \overline{B}(p, \frac{r}{2})} n_{\text{out}, \overline{B}(p, \frac{r}{2})}(q) \phi(q) dq$

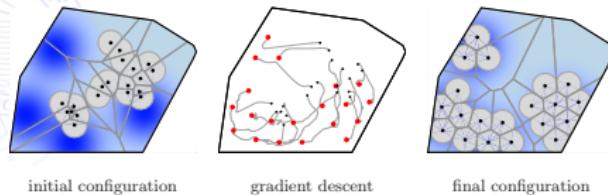
3:  $\lambda_* := \max\{\lambda \mid \delta \mapsto \int_{V \cap \overline{B}(p + \delta v, \frac{r}{2})} \phi(q) dq \text{ is strictly increasing on } [0, \lambda]\}$

4: return  $\lambda_* v$

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## Simulation



For  $r, \varepsilon \in \mathbb{R}_{>0}$ ,

$$T_{\varepsilon-r\text{-area-dply}}(P) = \begin{cases} \text{true,} & \text{if } \left\| \int_{V[p^i](P) \cap \partial \overline{B}(p^{[i]}, \frac{r}{2})} n_{\text{out}, \overline{B}(p^{[i]}, \frac{r}{2})}(q) \phi(q) dq \right\|_2 \leq \varepsilon, i \in \{1, \dots, n\} \\ \text{false,} & \text{otherwise.} \end{cases}$$

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## LMTD-VRN-CNTRD algorithm

Optimizes  $\mathcal{H}_{\text{distor-area}, \frac{r}{2}}$

**Robotic Network:**  $S_{\text{LD}}$  in  $Q$  with absolute sensing of own position, and with communication range  $r$

**Distributed Algorithm:** LMTD-VRN-CNTRD

Alphabet:  $A = \mathbb{R}^d \cup \{\text{null}\}$

function  $\text{msg}(p, i)$

1: **return**  $p$

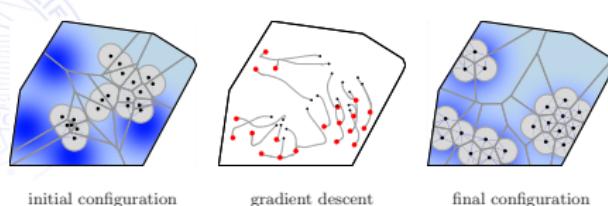
function  $\text{ctl}(p, y)$

1:  $V := Q \cap \overline{B}(p, \frac{r}{2}) \cap (\bigcap \{H_{p, p_{\text{rcvd}}} \mid \text{for all non-null } p_{\text{rcvd}} \in y\})$

2: **return**  $\text{CM}_\phi(V) - p$

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## Simulation



For  $r, \varepsilon \in \mathbb{R}_{>0}$ ,

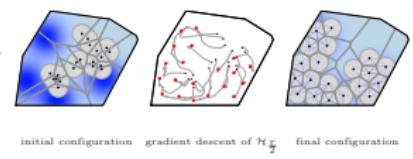
$$T_{\varepsilon-r\text{-distor-area-dply}}(P) = \begin{cases} \text{true,} & \text{if } \|p^{[i]} - \text{CM}_\phi(V_{\frac{r}{2}}^{[i]}(P))\|_2 \leq \varepsilon, i \in \{1, \dots, n\}, \\ \text{false,} & \text{otherwise.} \end{cases}$$

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## Optimizing $\mathcal{H}_{\text{distor}}$ via constant-factor approximation

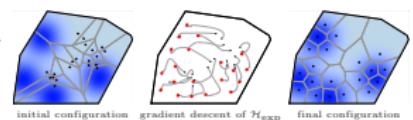
### Limited range

run #1: 16 agents, density  $\phi$  is sum of 4 Gaussians, time invariant, 1st order dynamics



### Unlimited range

run #2: 16 agents, density  $\phi$  is sum of 4 Gaussians, time invariant, 1st order dynamics



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**Theorem**

For  $d \in \mathbb{N}$ ,  $r \in \mathbb{R}_{>0}$  and  $\varepsilon \in \mathbb{R}_{>0}$ , the following statements hold.

- 1 on the network  $\mathcal{S}_{\text{D}}$ , the law  $\mathcal{CC}_{\text{VRN-CNTRD}}$  and on the network  $\mathcal{S}_{\text{vehicles}}$ , the law  $\mathcal{CC}_{\text{VRN-CNTRD-DYNAMCS}}$  both achieve the  $\varepsilon$ -distortion deployment task  $T_{\varepsilon\text{-distor-dply}}$ . Moreover, any execution of  $\mathcal{CC}_{\text{VRN-CNTRD}}$  and  $\mathcal{CC}_{\text{VRN-CNTRD-DYNMCS}}$  monotonically optimizes the multicenter function  $\mathcal{H}_{\text{distor}}$ ;
- 2 on the network  $\mathcal{S}_{\text{LD}}$ , the law  $\mathcal{CC}_{\text{LMTD-VRN-NRM}}$  achieves the  $\varepsilon$ -r-area deployment task  $T_{\varepsilon\text{-r-area-dply}}$ . Moreover, any execution of  $\mathcal{CC}_{\text{LMTD-VRN-NRM}}$  monotonically optimizes the multicenter function  $\mathcal{H}_{\text{area}, \frac{\varepsilon}{2}}$ ; and
- 3 on the network  $\mathcal{S}_{\text{LD}}$ , the law  $\mathcal{CC}_{\text{LMTD-VRN-CNTRD}}$  achieves the  $\varepsilon$ -r-distortion-area deployment task  $T_{\varepsilon\text{-r-distor-area-dply}}$ . Moreover, any execution of  $\mathcal{CC}_{\text{LMTD-VRN-CNTRD}}$  monotonically optimizes the multicenter function  $\mathcal{H}_{\text{distor-area}, \frac{\varepsilon}{2}}$ .

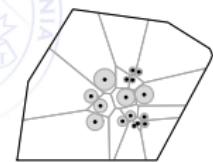
Assume  $\text{diam}(Q)$  is independent of  $n$ ,  $r$  and  $\varepsilon$

**Theorem (Time complexity of LMTD-VRN-CNTRD law)**

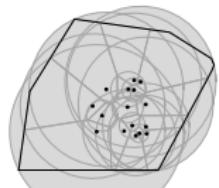
Assume the robots evolve in a closed interval  $Q \subset \mathbb{R}$ , that is,  $d = 1$ , and assume that the density is uniform, that is,  $\phi \equiv 1$ . For  $r \in \mathbb{R}_{>0}$  and  $\varepsilon \in \mathbb{R}_{>0}$ , on the network  $\mathcal{S}_{\text{LD}}$

$$\text{TC}(T_{\varepsilon\text{-r-distor-area-dply}}, \mathcal{CC}_{\text{LMTD-VRN-CNTRD}}) \in O(n^3 \log(ne^{-1}))$$

## Deployment: basic behaviors



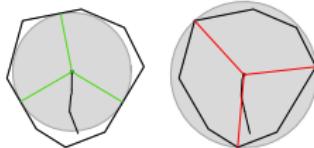
**“move away from closest”**



**“move towards furthest”**

Equilibria? Asymptotic behavior?  
Optimizing network-wide function?

## Deployment: 1-center optimization problems



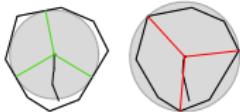
$$\begin{aligned} \text{sm}_Q(p) &= \min\{\|p - q\| \mid q \in \partial Q\} && \text{Lipschitz} && 0 \in \partial \text{sm}_Q(p) \Leftrightarrow p \in \text{IC}(Q) \\ \text{lg}_Q(p) &= \max\{\|p - q\| \mid q \in \partial Q\} && \text{Lipschitz} && 0 \in \partial \text{lg}_Q(p) \Leftrightarrow p = \text{CC}(Q) \end{aligned}$$

Locally Lipschitz function  $V$  are differentiable a.e.

Generalized gradient of  $V$  is

$$\partial V(x) = \text{convex closure}\left\{\lim_{i \rightarrow \infty} \nabla V(x_i) \mid x_i \rightarrow x, x_i \notin \Omega_V \cup S\right\}$$

## Deployment: 1-center optimization problems



- + gradient flow of  $\text{sm}_Q \quad \dot{p}_i = + \text{Ln}[\partial \text{sm}_Q](p) \quad \text{"move away from closest"}$
- gradient flow of  $\text{lg}_Q \quad \dot{p}_i = - \text{Ln}[\partial \text{lg}_Q](p) \quad \text{"move toward furthest"}$

For  $X$  essentially locally bounded, Filippov solution of  $\dot{x} = X(x)$  is absolutely continuous function  $t \in [t_0, t_1] \mapsto x(t)$  verifying

$$\dot{x} \in K[X](x) = \text{co}\{\lim_{i \rightarrow \infty} X(x_i) \mid x_i \rightarrow x, x_i \notin S\}$$

For  $V$  locally Lipschitz, gradient flow is  $\dot{x} = \text{Ln}[\partial V](x)$   
 $\text{Ln}$  = least norm operator

## Nonsmooth LaSalle Invariance Principle

Evolution of  $V$  along Filippov solution  $t \mapsto V(x(t))$  is differentiable a.e.

$$\frac{d}{dt} V(x(t)) \in \underbrace{\tilde{\mathcal{L}}_X V(x(t))}_{\text{set-valued Lie derivative}} = \{a \in \mathbb{R} \mid \exists v \in K[X](x) \text{ s.t. } \zeta \cdot v = a, \forall \zeta \in \partial V(x)\}$$

### LaSalle Invariance Principle

For  $S$  compact and strongly invariant with  $\max \tilde{\mathcal{L}}_X V(x) \leq 0$

Any Filippov solution starting in  $S$  converges to largest weakly invariant set contained in  $\{x \in S \mid 0 \in \tilde{\mathcal{L}}_X V(x)\}$

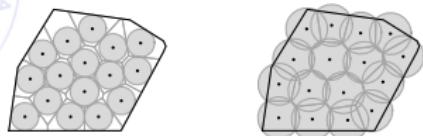
E.g., nonsmooth gradient flow  $\dot{x} = -\text{Ln}[\partial V](x)$  converges to critical set

## Deployment: multi-center optimization

sphere packing and disk covering

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- "move away from closest":  $\dot{p}_i = + \text{Ln}(\partial \text{sm}_{V_i(P)})(p_i) \quad \text{--- at fixed } V_i(P)$
- "move towards furthest":  $\dot{p}_i = - \text{Ln}(\partial \text{lg}_{V_i(P)})(p_i) \quad \text{--- at fixed } V_i(P)$



Aggregate objective functions!

$$\mathcal{H}_{\text{sp}}(P) = \min_i \text{sm}_{V_i(P)}(p_i) = \min_{i \neq j} \left[ \frac{1}{2} \|p_i - p_j\|, \text{dist}(p_i, \partial Q) \right]$$

$$\mathcal{H}_{\text{dc}}(P) = \max_i \text{lg}_{V_i(P)}(p_i) = \max_{q \in Q} \left[ \min_i \|q - p_i\| \right]$$

## Deployment: multi-center optimization

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Critical points of  $\mathcal{H}_{\text{sp}}$  and  $\mathcal{H}_{\text{dc}}$  (locally Lipschitz)

- If  $0 \in \text{int}(\partial \mathcal{H}_{\text{sp}}(P))$ , then  $P$  is strict local maximum, all agents have same cost, and  $P$  is **incenter Voronoi configuration**
- If  $0 \in \text{int}(\partial \mathcal{H}_{\text{dc}}(P))$ , then  $P$  is strict local minimum, all agents have same cost, and  $P$  is **circumcenter Voronoi configuration**

Aggregate functions **monotonically optimized** along evolution

$$\min \tilde{\mathcal{L}}_{\text{Ln}(\partial \text{sm}_{V_0})} \mathcal{H}_{\text{sp}}(P) \geq 0$$

$$\max \tilde{\mathcal{L}}_{-\text{Ln}(\partial \text{lg}_{V_0})} \mathcal{H}_{\text{dc}}(P) \leq 0$$

**Asymptotic convergence** to center Voronoi configurations via nonsmooth LaSalle

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**Robotic Network:**  $\mathcal{S}_D$  in  $Q$  with absolute sensing of own position

**Distributed Algorithm:** VRN-CRCMCNTR

Alphabet:  $A = \mathbb{R}^d \cup \{\text{null}\}$

function  $\text{msg}(p, i)$

1: return  $p$

function  $\text{ctl}(p, y)$

1:  $V := Q \cap (\bigcap \{H_{p, p_{\text{recv}}} \mid \text{for all non-null } p_{\text{recv}} \in y\})$

2: return  $\text{CC}(V) - p$

**Robotic Network:**  $\mathcal{S}_D$  in  $Q$ , with absolute sensing of own position

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1:  $V := Q \cap (\bigcap \{H_{p, p_{\text{recv}}} \mid \text{for all non-null } p_{\text{recv}} \in y\})$

2: return  $x \in \text{IC}(V) - p$

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## Correctness of the geometric-center algorithms

For  $\varepsilon \in \mathbb{R}_{>0}$ , the  $\varepsilon$ -disk-covering deployment task

$$\mathcal{T}_{\varepsilon\text{-dc-dply}}(P) = \begin{cases} \text{true}, & \text{if } \|p^{[i]} - \text{CC}(V^{[i]}(P))\|_2 \leq \varepsilon, \quad i \in \{1, \dots, n\}, \\ \text{false}, & \text{otherwise,} \end{cases}$$

For  $\varepsilon \in \mathbb{R}_{>0}$ , the  $\varepsilon$ -sphere-packing deployment task

$$\mathcal{T}_{\varepsilon\text{-sp-dply}}(P) = \begin{cases} \text{true}, & \text{if } \text{dist}_2(p^{[i]}, \text{IC}(V^{[i]}(P))) \leq \varepsilon, \quad i \in \{1, \dots, n\}, \\ \text{false}, & \text{otherwise,} \end{cases}$$

### Theorem

For  $d \in \mathbb{N}$ ,  $r \in \mathbb{R}_{>0}$  and  $\varepsilon \in \mathbb{R}_{>0}$ , the following statements hold.

- 1 on the network  $\mathcal{S}_D$ , any execution of the law  $\text{CC}_{\text{VRN-CRCMCNTR}}$  monotonically optimizes the multicenter function  $\mathcal{H}_{\text{dc}}$ ;
- 2 on the network  $\mathcal{S}_D$ , any execution of the law  $\text{CC}_{\text{VRN-NCNTR}}$  monotonically optimizes the multicenter function  $\mathcal{H}_{\text{sp}}$ .

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## Summary and conclusions

Aggregate objective functions

- 1 variety of scenarios: expected-value, disk-covering, sphere-packing
- 2 smoothness properties and gradient information
- 3 geometric-center control and communication laws

### Technical tools

- 1 Geometric optimization
- 2 Geometric models, proximity graphs, spatially-distributed maps
- 3 Systems theory, nonsmooth stability analysis

## References

### Deployment scenarios and algorithms:

- J. Cortés, S. Martínez, T. Karatas, and F. Bullo. Coverage control for mobile sensing networks. *IEEE Transactions on Robotics and Automation*, 20(2):243–255, 2004
- J. Cortés, S. Martínez, and F. Bullo. Spatially-distributed coverage optimization and control with limited-range interactions. *ESAIM: Control, Optimisation & Calculus of Variations*, 11:691–719, 2005

### Nonsmooth stability analysis:

- J. Cortés. Discontinuous dynamical systems -- a tutorial on solutions, nonsmooth analysis, and stability. *IEEE Control Systems Magazine*, 28(3):36–73, 2008

### Geometric and combinatorial optimization:

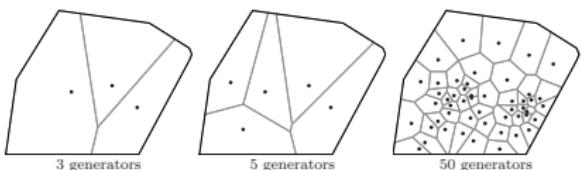
- P. K. Agarwal and M. Sharir. Efficient algorithms for geometric optimization. *ACM Computing Surveys*, 30(4):412–458, 1998

## Voronoi partitions

Let  $(p_1, \dots, p_n) \in Q^n$  denote the positions of  $n$  points

The Voronoi partition  $\mathcal{V}(P) = \{V_1, \dots, V_n\}$  generated by  $(p_1, \dots, p_n)$

$$\begin{aligned} V_i &= \{q \in Q \mid \|q - p_i\| \leq \|q - p_j\|, \forall j \neq i\} \\ &= Q \cap_j \mathcal{HP}(p_i, p_j) \quad \text{where } \mathcal{HP}(p_i, p_j) \text{ is half plane } (p_i, p_j) \end{aligned}$$



◀ Return

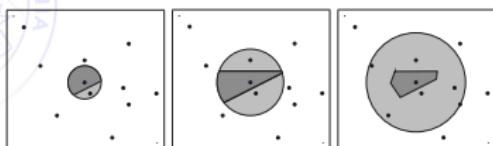
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## Distributed Voronoi computation

Assume: agent with sensing/communication radius  $R_i$

Objective: smallest  $R_i$  which provides sufficient information for  $V_i$



For all  $i$ , agent  $i$  performs:

- 1: initialize  $R_i$  and compute  $\hat{V}_i = \bigcap_{j: \|p_i - p_j\| \leq R_i} \mathcal{HP}(p_i, p_j)$
- 2: while  $R_i < 2 \max_{q \in \hat{V}_i} \|p_i - q\|$  do
- 3:      $R_i := 2R_i$
- 4:     detect vehicles  $p_j$  within radius  $R_i$ , recompute  $\hat{V}_i$

◀ Return

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