

Ergodic control using diffusion, HEDAC

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[MM09] and [MM11] define the coverage as a distribution in the domain $\Omega \subset \mathbb{R}^2$ using convolution of $\delta(\mathbf{x})$ Dirac delta function:

$$c_{smc}(\mathbf{x}) = \frac{1}{Nt} \sum_{i=1}^N \int_0^t \delta(\mathbf{x} - \mathbf{z}_i(\tau)) d\tau,$$

SMC motion control:

$$\frac{d\mathbf{z}_i}{dt} = \sum_{\mathbf{k}} \Lambda(\mathbf{k}) (m_{\mathbf{k}} - c_{\mathbf{k}}) \nabla f_{\mathbf{k}}(\mathbf{z}_i(t))$$

Velocity
(Change of direction)

Weights The difference of
Fourier coefficients

Gradient of Fourier basis
function at current location

A spectral-based smoothing:

$$\Lambda(\mathbf{k}) = \frac{1}{(1 + \|\mathbf{k}\|^2)^{\frac{n+1}{2}}}$$

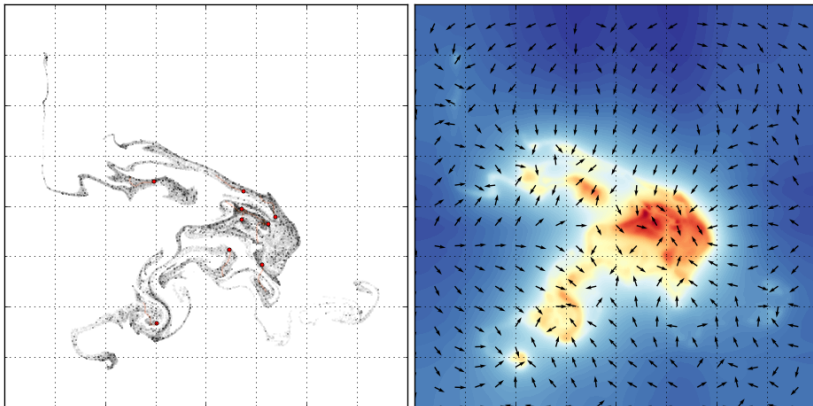
[MM09] George Mathew and Igor Mezić. "Spectral multiscale coverage: A uniform coverage algorithm for mobile sensor networks". In: *Proceedings of the 48th IEEE Conference on Decision and Control* (2009), pp. 7872–7877

[MM11] George Mathew and Igor Mezić. "Metrics for ergodicity and design of ergodic dynamics for multi-agent systems". In: *Physica D: Nonlinear Phenomena* 240.4-5 (2011), pp. 432–442


One can easily construct an attracting field (not only gradients at agents' current locations):

$$s(\mathbf{x}) = m(\mathbf{x}) - c(\mathbf{x})$$

$$u(\mathbf{x}) = \sum_{\mathbf{k}} \Lambda(\mathbf{k}) s_{\mathbf{k}} f_{\mathbf{k}}(\mathbf{x}),$$



SMC has some nice features/extensions:

- Good balance between local and global coverage
- Solid and robust convergence
- Applicable for different motion models (constraints?)
- It can be applied to dynamically alternated goal distribution $m(\mathbf{x}, t)$ [MSM10]
- MH370 search application , [Ivi+20]

But there are some limits:

- Does not acknowledge the "reach" of the kernel function γ
- Accomplished paths create artificial barriers (broad exploration due to $m - c < 0$)
- Limited to rectangular domains
- Difficult to consider obstacles

[MSM10] George Mathew, Amit Surana, and Igor Mezić. "Uniform coverage control of mobile sensor networks for dynamic target detection". In: IEEE. 2010, pp. 7292–7299

[Ivi+20] S. Ivić et al. "Search strategy in a complex and dynamic environment: the MH370 case". In: *Scientific reports* 10.1 (2020), pp. 1–15

Introducing radial basis kernel function

If sensing function γ is a positive, smooth and scalable (σ) local Radial Basis Function that satisfy:

$$\int_{\mathbb{R}^n} \gamma_{\sigma}(\mathbf{r}) \, d\mathbf{r} = 1,$$

with known agent trajectories, the coverage density at time \mathbf{t} can be defined as:

$$\tilde{c}_{\sigma}(\mathbf{x}, \mathbf{t}) = \frac{1}{N\mathbf{t}} \sum_{i=1}^N \int_0^{\mathbf{t}} \gamma_{\sigma}(\mathbf{x} - \mathbf{z}_i(\tau)) \, d\tau.$$

When observing the γ in the limit $\sigma \rightarrow 0$:

$$\lim_{\sigma \rightarrow 0} \gamma_{\sigma}(\mathbf{r}) = \lim_{\sigma \rightarrow 0} \sigma^{-n} \gamma\left(\frac{\mathbf{r}}{\sigma}\right) = \delta(\mathbf{r}).$$

the coverage function will become a distribution [ICM16]:

$$\lim_{\sigma \rightarrow 0} c_{\sigma}(\mathbf{x}) = c_{smc}(\mathbf{x})$$

Introducing radial basis kernel function

Easy to incorporate in SMC algorithm: \mathbf{c}_k are obtained with FFT on the field c_σ

```
xmg, ymg = numpy.meshgrid(x, y)
c = np.zeros([ny, nx])
for p in points:
    c += numpy.exp(- ((xmg - p[0]) ** 2 + (ymg - p[1]) ** 2) / (2 * sigma ** 2))
```

Spectral smoothing and attraction field

```
scipy.fftpack import dct, idct
s = c - m
s[s < 0] = 0 # Comment line for original SMC formulation
s_k = dct(dct(s.T, norm='ortho').T, norm='ortho')

# Smoothing
ky, kx = numpy.meshgrid(numpy.arange(ny), numpy.arange(nx))
u_k = 1.0 / (1 + kx ** 2 + ky ** 2) ** 1.5 * s_k.T
# Obtain u
u = idct(idct(u_k.T, norm='ortho').T, norm='ortho')

vy, vx = numpy.gradient(self.U)
```

Heat Equation Driven Area Coverage (HEDAC)

- Adopts the attraction field approach from SMC [ICM16]
- Modeling the potential field via the stationary 2D PDE heat equation (Helmholtz equation)

$$\alpha \cdot \frac{\partial^2 u}{\partial \mathbf{x}^2} + \mathbf{s} - \beta \cdot u = 0$$

Conduction (diffusion) heat (source) cooling (sink)

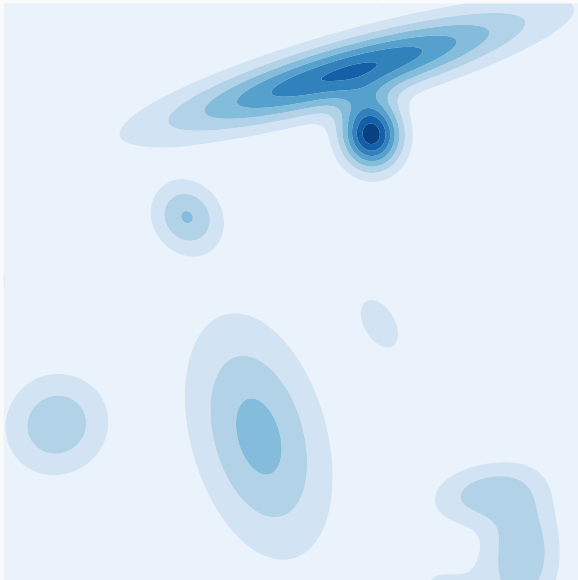
with Neumann boundary conditions:

$$\left. \frac{\partial u}{\partial \mathbf{n}} \right|_{\Gamma} = 0$$

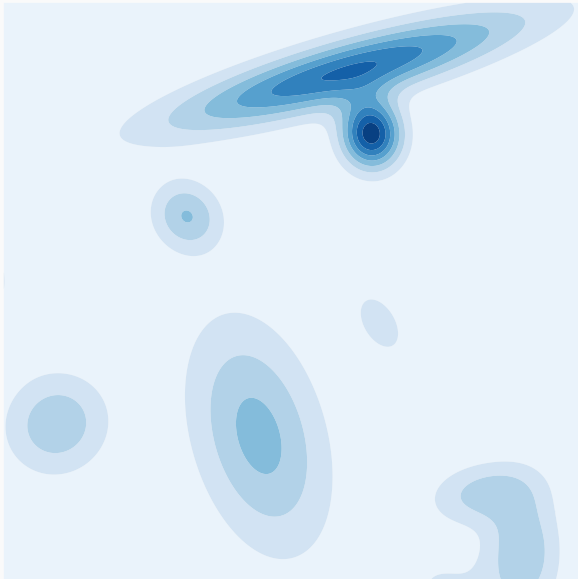
insulation

- The difference between achieved and goal density $\mathbf{s} = \max(\mathbf{m} - \mathbf{c}, \mathbf{0})$ acts as a heat/potential source
- Resulting potential u is "similar" to the source \mathbf{s} (smoothing, gradient)
- Physical interpretation and intuition
- Why stationary?

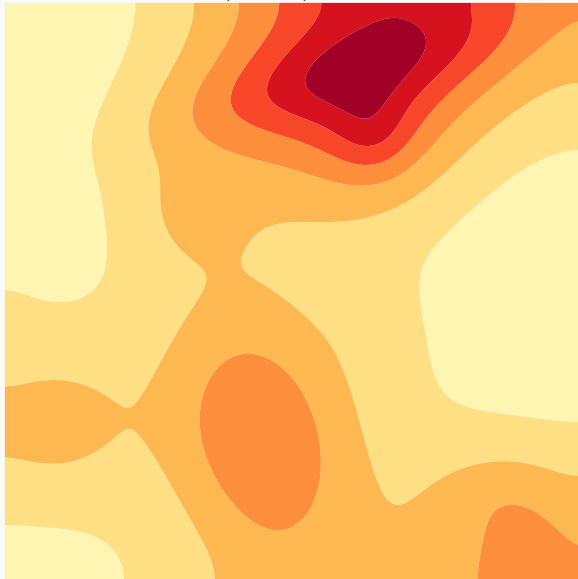
Source, $\max(m - c, 0)$



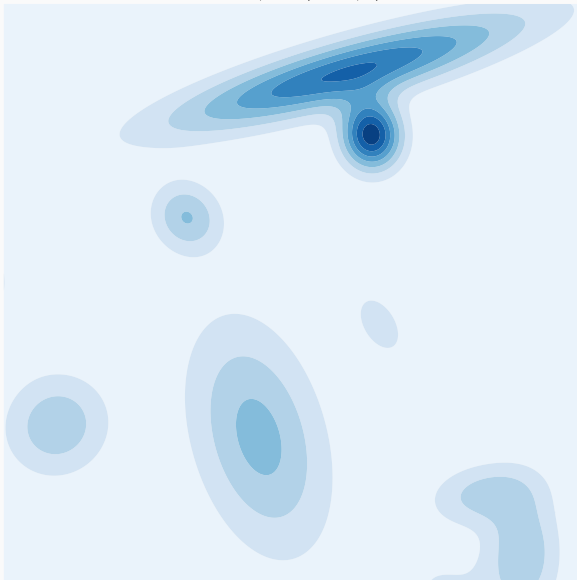
Source, $\max(m - c, 0)$



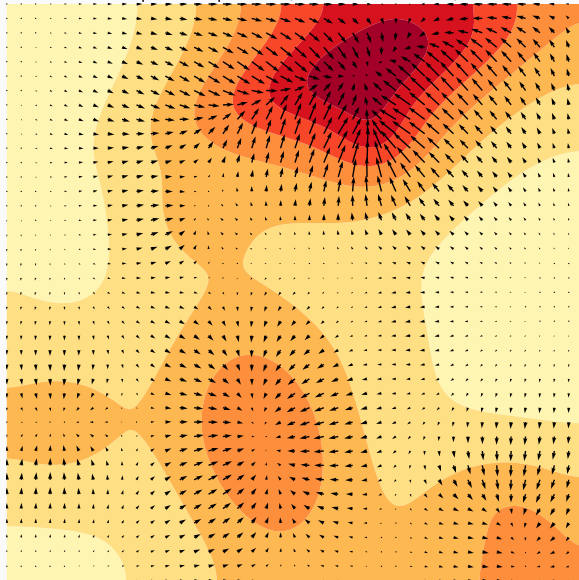
Temperature/potential, u



Source, $\max(m - c, 0)$



Temperature/potential, $u \gg \gg$ Gradient, ∇u






Motion control is established via a feedback loop:

$$\alpha \cdot \frac{\partial^2 \mathbf{u}}{\partial \mathbf{x}^2} + \mathbf{s} - \beta \cdot \mathbf{u} = \mathbf{0},$$

$$\mathbf{c}(\mathbf{x}, t) = \frac{1}{Nt} \sum_{i=1}^N \int_0^t \gamma_{\sigma}(\mathbf{x} - \mathbf{z}_i(\tau)) d\tau,$$

$$\frac{d\mathbf{z}_i}{dt} = \mathbf{v}_a \cdot \frac{\nabla u(\mathbf{z}_i(t))}{|\nabla u(\mathbf{z}_i(t))|}$$

- General coverage [ICM16]:
 - Uniform 
 - Nonuniform 
- *Drawing without lifting the pen from the paper* (unpublished) 

PDE:

$$\begin{aligned}
 & \alpha \cdot \frac{\partial^2 u}{\partial \mathbf{x}^2} + m - \beta \cdot u = 0 \\
 & \quad \quad \quad \Downarrow \quad \quad \quad \Downarrow \quad \quad \quad \Downarrow \\
 & \alpha \cdot \left(\frac{u_{i-1,j} - 2u_{i,j} + u_{i+1,j}}{\Delta x^2} + \frac{u_{i,j-1} - 2u_{i,j} + u_{i,j+1}}{\Delta y^2} \right) + m(x_{i,j}) - \beta \cdot u_{i,j} = 0 \\
 & \quad \quad \quad \text{for } i = 1, \dots, n_x - 1, j = 1, \dots, n_y - 1.
 \end{aligned}$$

BC:

$$\begin{aligned}
 & \left. \frac{\partial u}{\partial \mathbf{n}} \right|_{\Gamma} = 0 \\
 & \quad \quad \quad \Downarrow \\
 & \frac{u_{1,j} - u_{0,j}}{\Delta x} = 0, \quad \frac{u_{n_x,j} - u_{n_x-1,j}}{\Delta x} = 0, \quad \text{for } j = 1, \dots, n_y - 1 \\
 & \frac{u_{i,1} - u_{i,0}}{\Delta x} = 0, \quad \frac{u_{i,n_y} - u_{i,n_y-1}}{\Delta x} = 0 \quad \text{for } i = 1, \dots, n_x - 1.
 \end{aligned}$$

Solution \mathbf{u} is obtained by solving linear system

$$\mathbf{A} \cdot \mathbf{u} = \mathbf{b}(m)$$

Matrix \mathbf{A} is constant:

$$\mathbf{u} = \mathbf{A}^{-1} \cdot \mathbf{b}(m)$$

which allows computationally efficient implementation.

```
# Inializtion
A = numpy.zeros((nx * ny, nx * ny))
b = numpy.zeros(nx * ny)
# ... populate system matrix A
invA = numpy.linalg.inv(A)

# Time loop
# ... update vector b (according to current coverage)
u = numpy.dot(A, b) # Solve potential u
```

```
# Inializtion
A = scipy.sprse.lil_matrix((nx * ny, nx * ny))
b = np.zeros(nx * ny)
# ... populate system matrix A
A = A.tocsc()
lu = scipy.sparse.linalg.splu(A)

# Time loop
# ... update vector b (according to current coverage)
u = lu.solve(b) # Solve potential
```

References

- ▶ George Mathew and Igor Mezić. “Spectral multiscale coverage: A uniform coverage algorithm for mobile sensor networks”. In: *Proceedings of the 48th IEEE Conference on Decision and Control* (2009), pp. 7872–7877.
- ▶ George Mathew, Amit Surana, and Igor Mezić. “Uniform coverage control of mobile sensor networks for dynamic target detection”. In: IEEE. 2010, pp. 7292–7299.
- ▶ George Mathew and Igor Mezić. “Metrics for ergodicity and design of ergodic dynamics for multi-agent systems”. In: *Physica D: Nonlinear Phenomena* 240.4-5 (2011), pp. 432–442.
- ▶ S. Ivić, B. Crnković, and I. Mezić. “Ergodicity-based cooperative multiagent area coverage via a potential field”. In: *IEEE transactions on cybernetics* 47.8 (2016), pp. 1983–1993.
- ▶ S. Ivić et al. “Search strategy in a complex and dynamic environment: the MH370 case”. In: *Scientific reports* 10.1 (2020), pp. 1–15.