

# Introduction to Ergodic Control

## ICRA 2024: Ergodic Control Tutorial Workshop

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- **Signal Analysis**
- **Dynamic Systems**

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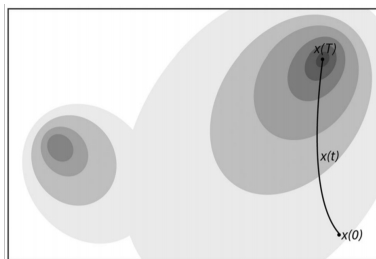
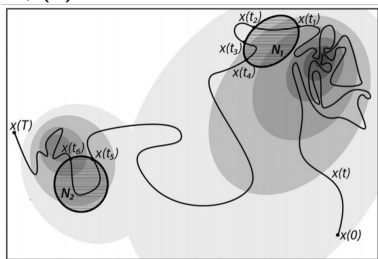
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In this workshop, we will be referring to the ergodicity of a trajectory  $x(t)$  with respect to a distribution  $\phi(x)$

# What makes a trajectory ergodic?

A trajectory is perfectly ergodic with respect to a distribution if the amount of time spent in a neighborhood  $\mathcal{N}$  of the state space is proportional to the spatial distribution in the neighborhood  $\int \mathcal{N} \phi(s) ds$ .

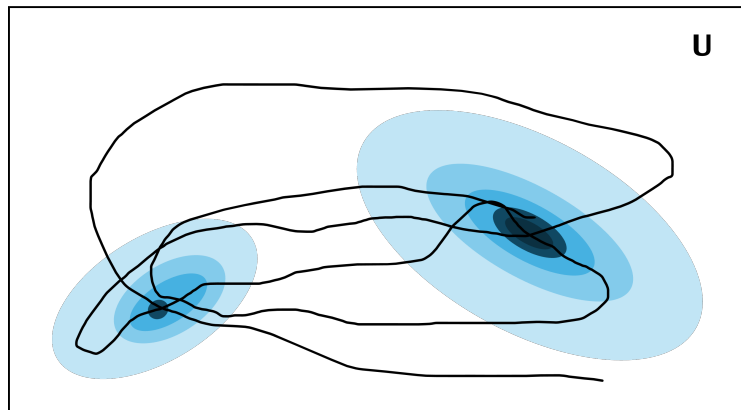


L.M. Miller and T.D. Murphey, Trans. Rob., vol. 32, no. 1, pp. 4196–4201, 2016



# Quantifying Ergodic trajectories

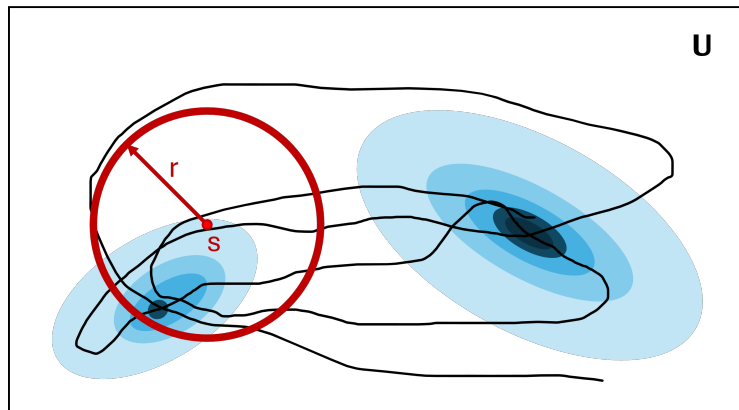
Given a trajectory and distribution in the rectangular domain  $U$



# Quantifying Ergodic trajectories

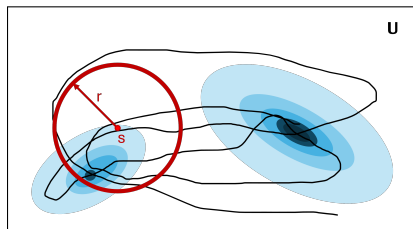
Given a trajectory and distribution in the rectangular domain  $U$

Define a set  $B(s, r)$  and  $I_{(s,r)}(y) = \begin{cases} 1 & \text{inside } B(s, r) \\ 0 & \text{o.w.} \end{cases}$



# Quantifying Ergodic trajectories

Given a trajectory and distribution in the rectangular domain  $U$



Define a set  $B(s, r)$  and

$$I_{(s,r)}(y) = \begin{cases} 1 & \text{inside } B(s, r) \\ 0 & \text{o.w.} \end{cases}$$

The average time spent in the set  $B(s, r)$  is

$$d^t(s, r) = \frac{1}{t} \int_0^t I_{(s,r)}(x(\tau)) d\tau.$$

The measure of the distribution on the same set is given by

$$\bar{\phi}(s, r) = \int_U \phi(y) I_{(s,r)}(y) dy.$$

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$$E^2(t) = \int_0^R \int_U (d^t(s, r) - \bar{\phi}(s, r))^2 ds dr, \quad R > 0.$$

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$$E^2(t) = \int_0^R \int_U (d^t(s, r) - \phi(s, r))^2 ds dr, \quad R > 0.$$

This **metric** tells us the **distance from ergodicity**



# Construct a trajectory distribution

Let's consider instead an alternative way to represent the trajectory, by constructing a distribution,

$$C(x) = \frac{1}{t} \int_0^t \delta(x - x(\tau)) d\tau,$$

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\*So we could rewrite average time spent in  $B(s, r)$  as

$$d^t(s, r) = \langle C, I_{(s,r)} \rangle$$

# Construct a trajectory distribution

Let's write the Fourier coefficients of  $x(t)$  as

$$c_k = \langle C, F_k \rangle = \frac{1}{T} \int_0^T F_k(x(t)) dt,$$

using Fourier basis functions of the form,

$$F_k(x(t)) = \frac{1}{h_k} \prod_{i=1}^n \cos\left(\frac{k_i \pi}{L_i} x_i(t)\right).$$

- $x(t)$  is  $n$ -dimensional
- $k$  is multi-index over the coefficients of the multi-dimensional Fourier transform
- $L_i$  is a measure of the length of the dimension.
- $h_k$  is a normalizing factor that make  $F_k$  an orthonormal basis

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In 2 dimensions,  $h_k$  takes the form,

$$h_k = \left( \int_0^{L_1} \int_0^{L_2} \cos^2\left(\frac{k_1 \pi}{L_1} x_1\right) \cos^2\left(\frac{k_2 \pi}{L_2} x_2\right) dx_1 dx_2 \right)^{1/2}.$$

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Now, the Fourier representations of  $C$  and  $\phi$  are in the same vector space.

The distance between  $C$  and  $\phi(x)$  is

$$\varepsilon(t) = \sum_{k_1=0}^K \dots \sum_{k_n=0}^K \Lambda_k |c_k - \phi_k|^2$$

The coefficient  $\Lambda_k = (1 + \|k\|^2)^{-s}$  where  $s = \frac{n+1}{2}$  places larger weights on lower frequency information.



Requiring

$$\lim_{t \rightarrow \infty} \varepsilon = 0$$

is equivalent to requiring the time average of the **trajectory** to converge to the spatial averages of **distribution**.

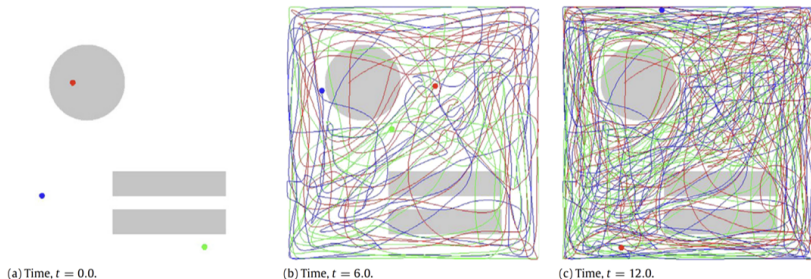
It can be shown that  $\varepsilon(t)$  and  $E(t)$  are equivalent metrics, since there exists bounded constants such that

$$C_1 \varepsilon(t) \leq E^2(t) \leq C_2 \varepsilon(t).$$

# Spectral Multiscale Coverage

If the aim is to control agents with linear dynamics to cover a region uniformly, one can design a feedback law that drives the agents to take actions that maximize the rate of decay of the ergodic metric.

*G. Mathew, I. Mezić / Physica D 240 (2011) 432–442*



# Ergodic Metric as a cost function

Given a system with dynamics,

$$\dot{x} = f(x(t), u(t)), \quad x(0) = x_0.$$

Instead of

$$J = \int_0^t l(x, u) dt = \int_0^t (x_d - x)^T Q (x_d - x) + u^T R u dt,$$

We use the ergodic metric

$$\begin{aligned} J(x(t), u(t)) &= q \varepsilon(x(t)) + \int_0^T u(t)^T R u(t) dt \\ &= q \sum_{k_1=0}^K \dots \sum_{k_n=0}^K \Lambda_k \left( \frac{1}{T} \int_0^T F_k(x(t)) dt - \phi_k \right)^2 \\ &\quad + \int_0^T u(t)^T R u(t) dt. \end{aligned}$$

# Derivative of an Ergodic Objective

We can find the gradient by taking the directional derivative of:

$$\begin{aligned} \frac{d}{d\epsilon} J(\xi + \epsilon\zeta)|_{\epsilon=0} = & \\ \frac{d}{d\epsilon} \left[ q \sum_{k=0}^K \Lambda_k \left( \frac{1}{T} \int_0^T F_k(x(s) + \epsilon z(s)) dt - \phi_k \right)^2 \right. & \\ \left. + \int_0^T (u(t) + \epsilon v(t))^T R(u(t) + \epsilon v(t)) dt \right]_{\epsilon=0} & \end{aligned}$$

# Derivative of an Ergodic Objective

Let's focus on the ergodic term for now

$$\frac{d}{d\epsilon} q \mathcal{E}(x(t) + \epsilon z(t))|_{\epsilon=0} =$$
$$\frac{d}{d\epsilon} \left[ q \sum_{k=0}^K \Lambda_k \left( \frac{1}{T} \int_0^T F_k(x(s) + \epsilon z(s)) dt - \phi_k \right)^2 \right]_{\epsilon=0}$$

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$$\frac{d}{d\epsilon} q \varepsilon(x(t) + \epsilon z(t))|_{\epsilon=0} =$$
$$\left[ q \sum_{k=0}^K \Lambda_k \left[ 2 \left( \frac{1}{T} \int_0^T F_k(x(s) + \epsilon z(s)) ds - \phi_k \right) \right. \right.$$
$$\left. \cdot \int_0^T \frac{1}{T} DF_k(x(t) + \epsilon z(t)) z(t) dt \right]_{\epsilon=0}$$

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$$\begin{aligned} DJ(\xi) \cdot \zeta = \int_0^T q \sum_{k=0}^K \Lambda_k \left[ 2 \left( \int_0^T \frac{1}{T} F_k(x(s)) ds - \phi_k \right) \right. \\ \left. \cdot \frac{1}{T} DF_k(x(t)) \right] \cdot z(t) + R(t)u(t) \cdot v(t) dt \end{aligned}$$



# Derivative of an Ergodic Objective

$$DJ(\xi) \cdot \zeta = \int_0^T q \sum_{k=0}^K \Lambda_k \left[ 2 \left( \int_0^T \frac{1}{T} F_k(x(s)) ds - \phi_k \right) \cdot \frac{1}{T} DF_k(x(t)) \right] \cdot z(t) + R(t)u(t) \cdot v(t) dt$$

When this derivative is close to zero, we have found a local extrema, and we can set up an LQ problem.

# Summary of the Spectral Ergodic Metric

Write the Fourier coefficients of  $x(t)$  as

$$c_k = \langle C, F_k \rangle = \frac{1}{T} \int_0^T F_k(x(t)) dt,$$

Using the same basis functions, we can compute the coefficients of the spatial distribution,

$$\phi_k = \langle \phi(x), F_k \rangle = \int_X \phi(x) F_k(x) dx$$

So the distance from perfect ergodicity is

$$\varepsilon(t) = \sum_{k_1=0}^K \dots \sum_{k_n=0}^K \Lambda_k |c_k - \phi_k|^2$$