

Introduction to Particle Swarm Optimization

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Next year: Who knows?

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- **A bit of biomimicry.**

Particle Swarm Optimizer (PSO) Fundamentals

Velocity of
 n -th particle

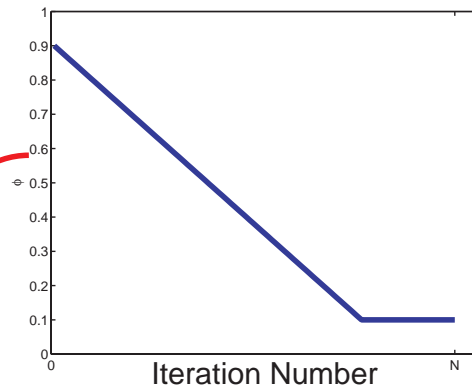
$$v_n(t + 1) = \phi(t) v_n(t) + \alpha_1 \gamma_{1n}(t) [p_n - x_n(t)] + \alpha_2 \gamma_{2n}(t) [G - x_n(t)] \quad (1)$$

Location of
 n -th particle

$$x_n(t + 1) = x_n(t) + v_n(t) \quad (2)$$

Particle Swarm Optimizer (PSO) Fundamentals

Inertia Function



$$v_n(t+1) = \phi(t) v_n(t) + \alpha_1 \gamma_{1n}(t) [p_n - x_n(t)] + \alpha_2 \gamma_{2n}(t) [G - x_n(t)] \quad (1)$$

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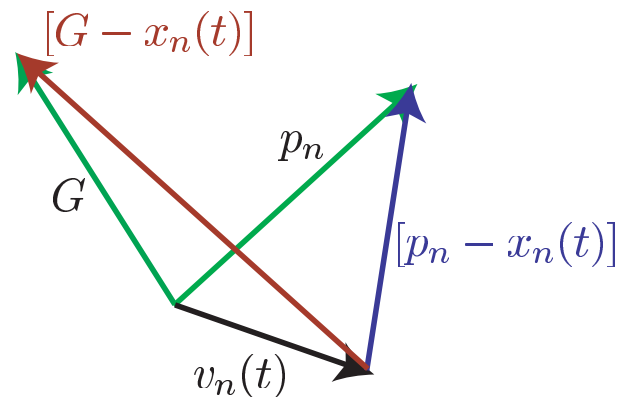
Position update

Particle Swarm Optimizer (PSO) Fundamentals

$$v_n(t+1) = \phi(t)v_n(t) + \alpha_1\gamma_{1n}(t)[p_n - x_n(t)] + \alpha_2\gamma_{2n}(t)[G - x_n(t)]$$

$$x_n(t+1) = x_n(t) + v_n(t)$$

Particle best position
Swarm global best position



Particle Swarm Optimizer (PSO) Fundamentals

$$v_n(t+1) = \phi(t)v_n(t) + \overset{\text{Acceleration constant}}{\alpha_1\gamma_{1n}(t)} [p_n - x_n(t)] + \overset{\text{Acceleration constant}}{\alpha_2\gamma_{2n}(t)} [G - x_n(t)] \quad (1)$$

$$x_n(t+1) = x_n(t) + v_n(t) \quad (2)$$

Particle Swarm Optimizer (PSO) Fundamentals

$$v_n(t+1) = \phi(t)v_n(t) + \alpha_1 \overset{\text{Random}}{\gamma_{1n}(t)} [p_n - x_n(t)] + \alpha_2 \overset{\text{Random}}{\gamma_{2n}(t)} [G - x_n(t)] \quad (1)$$

$$x_n(t+1) = x_n(t) + v_n(t) \quad (2)$$

Particle Swarm Optimizer (PSO) Fundamentals

$$v_n(t + 1) = \phi(t)v_n(t) + \alpha_1\gamma_{1n}(t) [p_n - x_n(t)] + \alpha_2\gamma_{2n}(t) [G - x_n(t)] \quad (1)$$

$$x_n(t + 1) = x_n(t) + v_n(t) \quad (2)$$

where

- n is the particle number;
- t is the time step;
- $x_n(t)$ is the location of the n -th particle at time t ;
- $v_n(t)$ is the velocity of the n -th particle at time t ;
- $\phi(t)$ is the “inertia” function;
- α_1 & α_2 are “acceleration” constants;
- $\gamma_{1n}(t)$ & $\gamma_{2n}(t)$ are $[0, 1]$ uniformly distributed random numbers;
- p_n is the n -th particle’s best location;
- G is the entire swarm’s best location

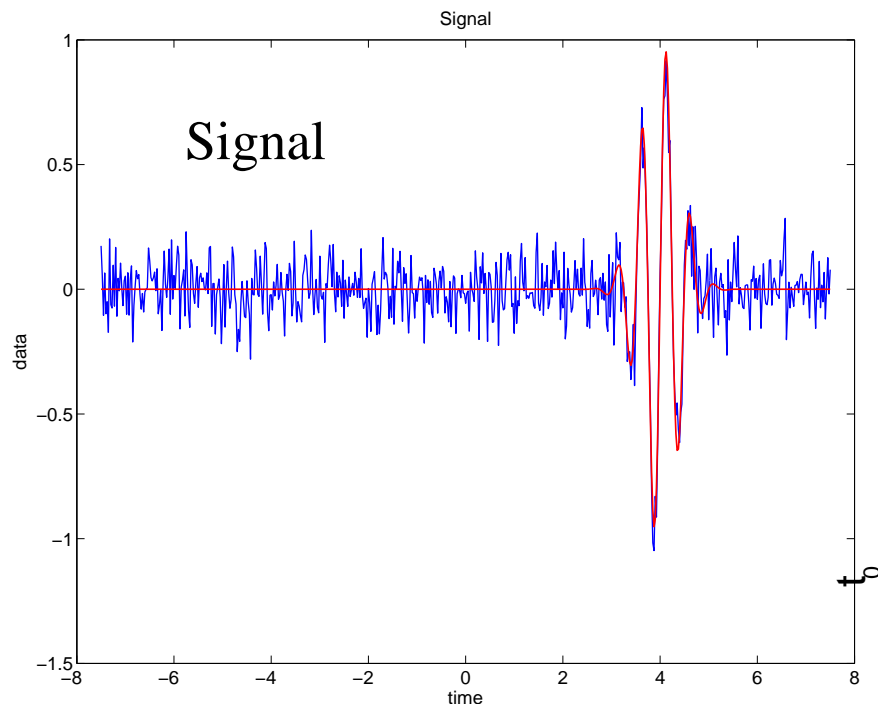
$x_n(t)$, $v_n(t)$, p_n , and G are N -dimensional vectors

Codes

- See www.mathworks.com user contributed codes;
- My `flight.m`

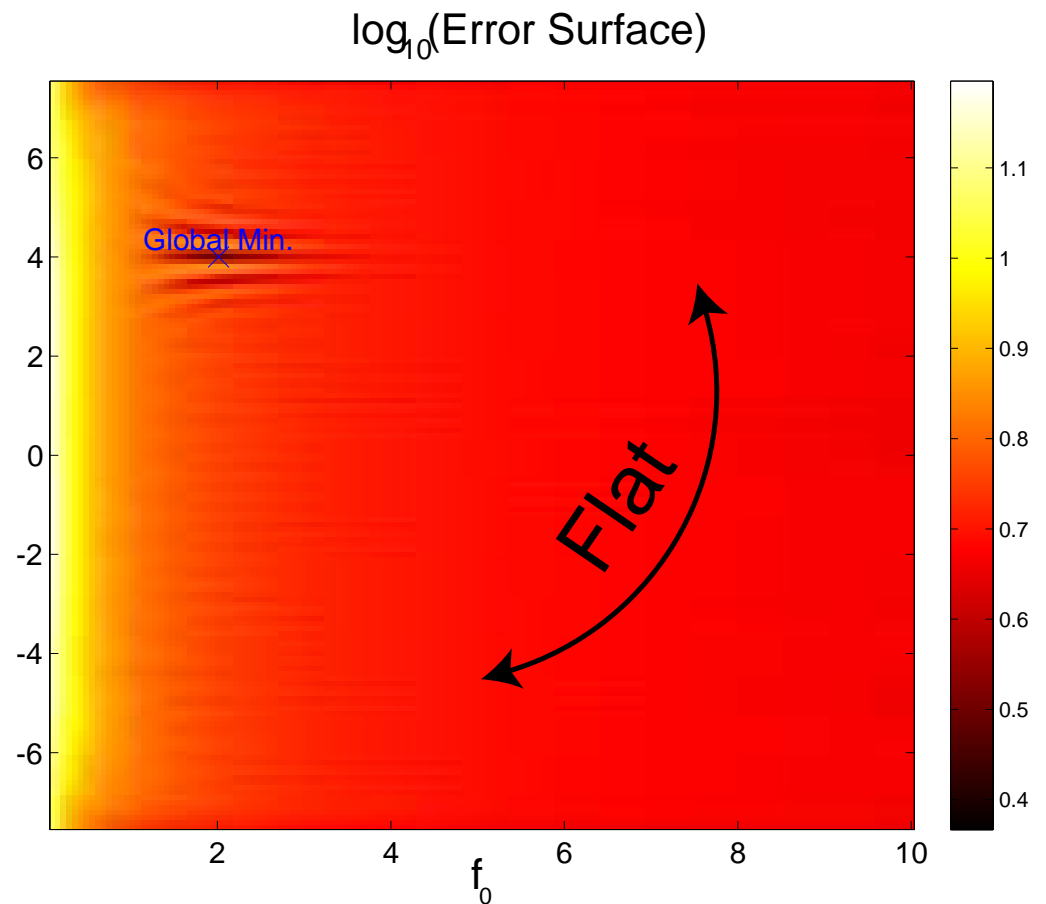
MATLAB example...

Determine Frequency & Time Shift Of Gaussian Windowed Sinusoid



Parameters to be determined:

- Frequency, $f_0 = 2$;
- Time Shift, $t_0 = 4$;
- 20 dB SNR.



Frequency & Time Shift Estimation Results

➤ PSO vs Gradient-based method (fminsearch);

➤ 5001 Monte Carlo runs;

➤ 20 dB SNR;

➤ Legend:

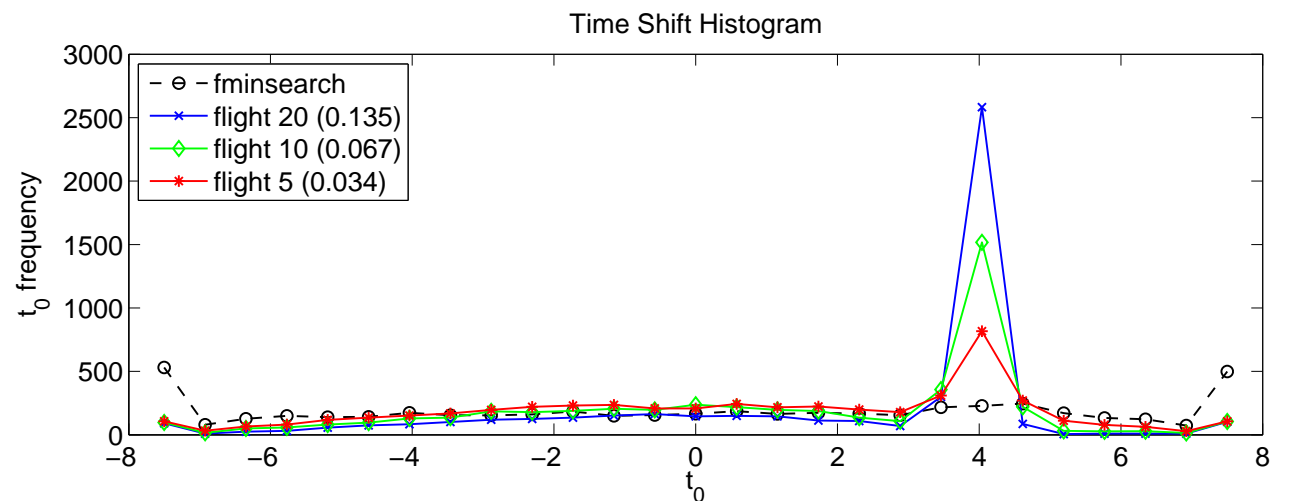
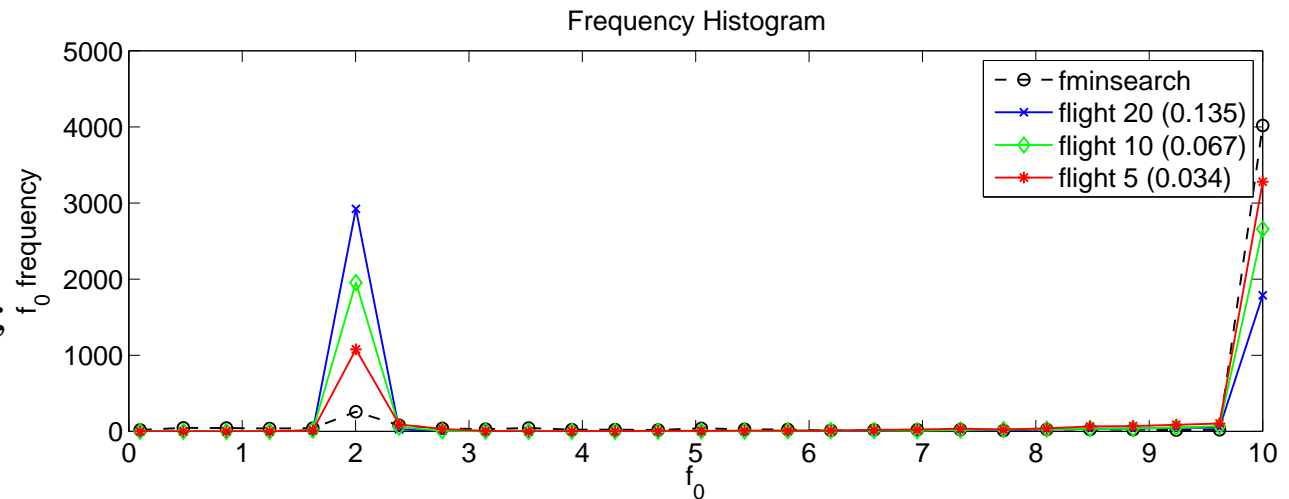
➤ Gradient-based method;

➤ 20 particles,
density of 0.14;

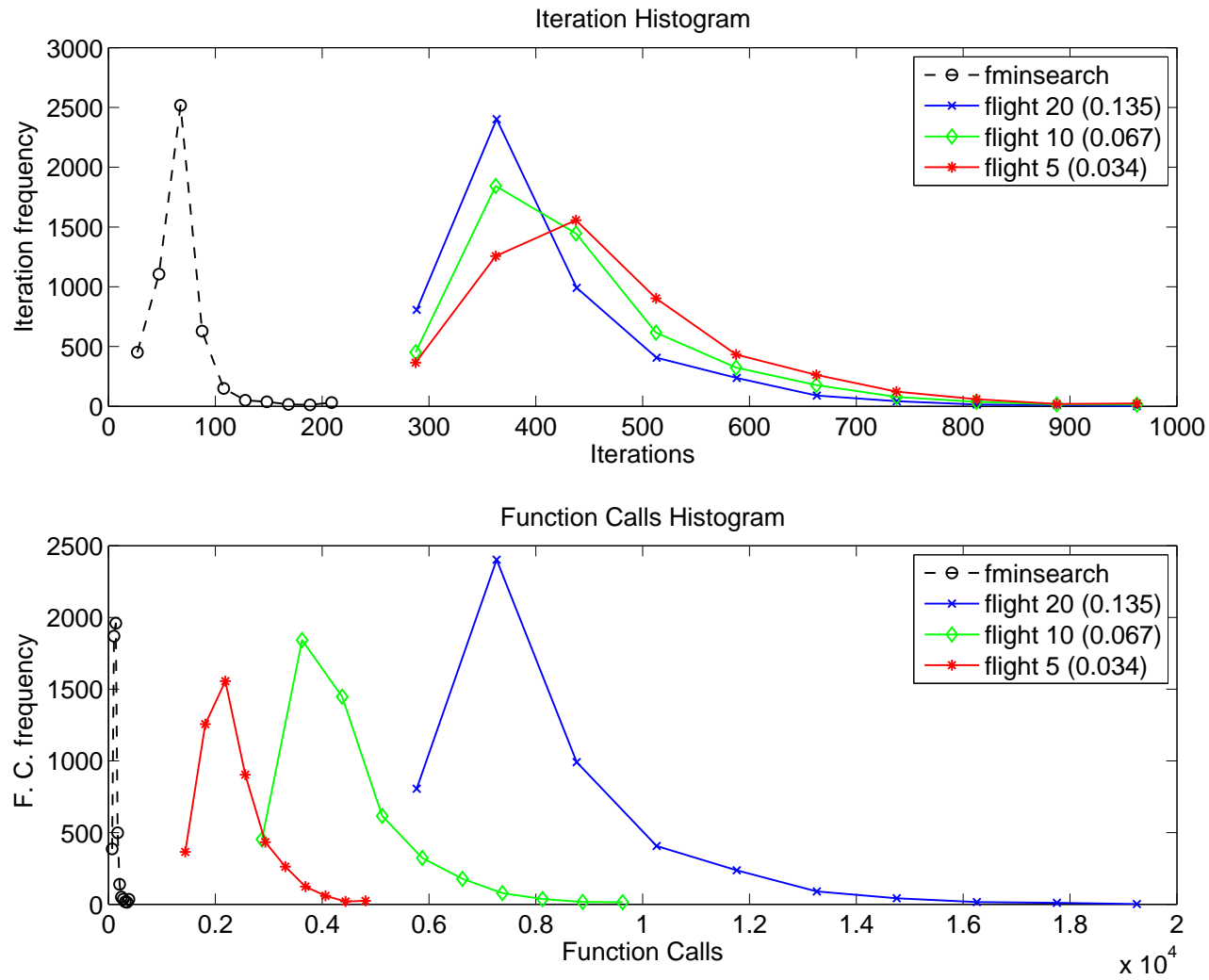
➤ 10 particles,
density of 0.07;

➤ 5 particles,
density of 0.03

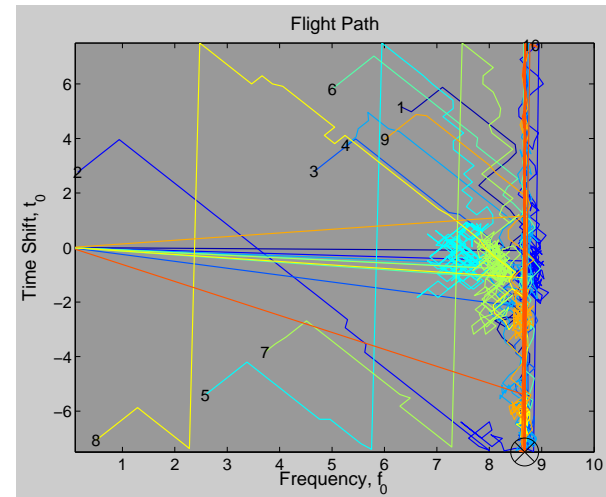
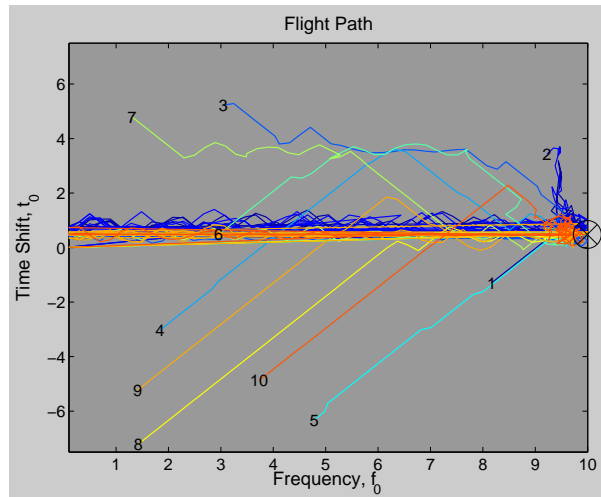
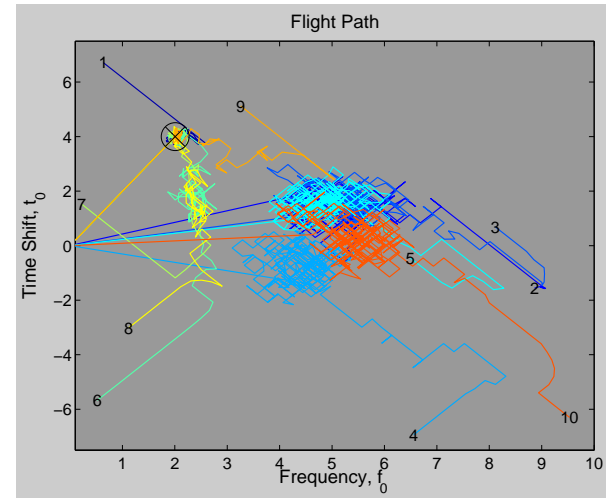
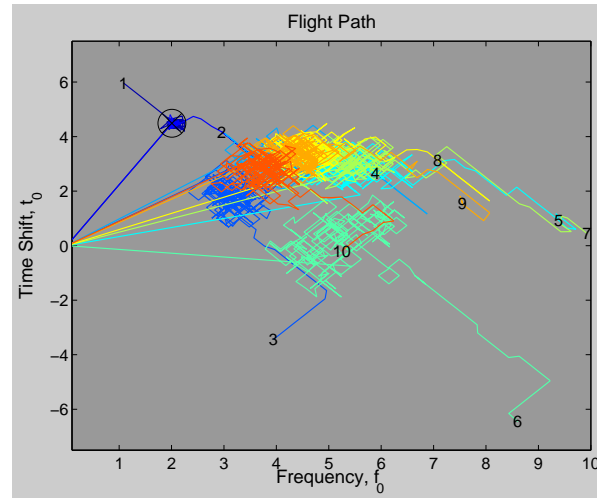
➤ flight out performs
fminsearch...



fminsearch Has Fewer Iterations & Function Calls



Sample Flight Paths



Conclusion

- If we had an infinite particle density, we could explore the space in one iteration;
- Short of that, use a “handful” of particles and terminate the flight early using the global best location as the initial guess for the gradient-based method.