



Real-Time Pedestrian Tracking with Bacterial Foraging Optimization

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9th Annual HUMIES Awards
GECCO 2012



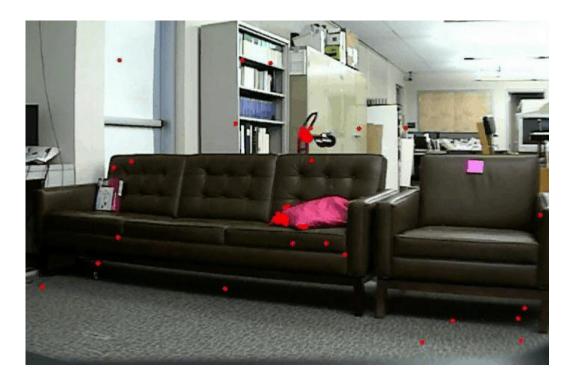
The Problem

- Track multiple pedestrians in low-resolution video
- Challenges include:
 - Change in appearance
 - Non-uniform lighting, shadows
 - Uncalibrated cameras
- Extremely useful for:
 - Security and surveillance applications
 - Human-computer interaction

Bacterial Foraging Optimization (BFO)

[Passino, MCS'02]

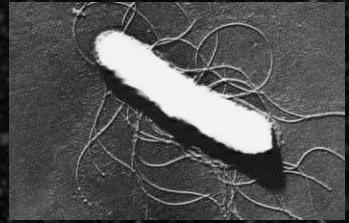
 Swarm intelligence algorithm modeled after foraging behavior of E. coli bacteria



Example: **Searching for a red object**

Foraging Behavior of E. coli

- Motile strains possess flagellum to "swim"
- "Tumbling" orients the bacterium into a random direction
- The bacterium swims in this direction and continues to as long as the concentration of food increases



Bacterial Foraging Optimization

- Randomly initialize n agents on the image
- For each frame, do k reproduction steps:
 - Do j chemotactic steps:
 - For each agent i, do this:
 - Evaluate fitness function at current location
 - Choose a random direction
 - For up to N_s times for this agent:
 - » Swim forward in a step of size C pixels
 - » Evaluate new fitness
 - » If new fitness is worse than old fitness, stop swimming
 - Sort agents by current fitness
 - Relocate S_r worst agents to position of S_r top agents
- Dispersal: randomly relocate agents with a $p_{ed}\%$ probability to a new random position in the image





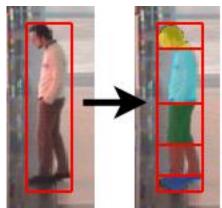
Improvements for Tracking

- Agents move 1 step forward and then evaluate, continuing if fitness stays constant or gets better, or stopping if worse
 - Introduced Lookahead
- In the same frame, all agents move at every reproduction step, including top agents of the previous iteration
 - Introduced *Elitism*
- Even if an object stops moving or does not move very far across frames, a full search is conducted every time
 - Introduced Early Termination

Initialization

- Detect head and shoulders using Viola-Jones framework or Omega-shape detector
- Extend rectangle of interest (ROI) down to estimate entire body (e.g., height = height*3.1)
- Segment body and create target signature





Head: 87-100%

Torso: 53.5-87%

Upper legs: 28.5-53.5%

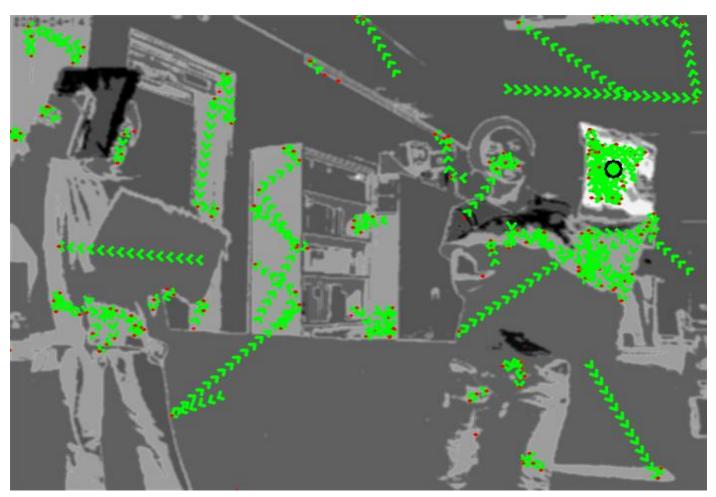
Lower legs: 0-28.5%

Feet: 0-10%

Visualizing the Fitness Space



Swarm's Behavior in Fitness Space



BFO = fast stochastic gradient hill climbing

darker = lower fitness, brighter = higher fitness

Experiments

$$is_tracked(ROI_{query}, ROI_{gt}) = \frac{ROI_{query} \cap ROI_{gt}}{ROI_{query} \cup ROI_{gt}} > 0.50$$

- i.e., tracking accuracy rate of "44%" means 26,000 of the 59,000 CAVIAR ROIs were correctly located with at least 50% groundtruth intersection
- **BFO:** 10 particles, 12 reproductions, 1 chemotactic step, 5 max swims per chemotaxis, 5px step size, 1 death/rebirth per reproduction, 90% dispersal rate
- **PSO:** 30 particles, 10 iterations

Dataset

 7 videos of the CAVIAR dataset considered to be the most difficult [Song, ECCV'10]



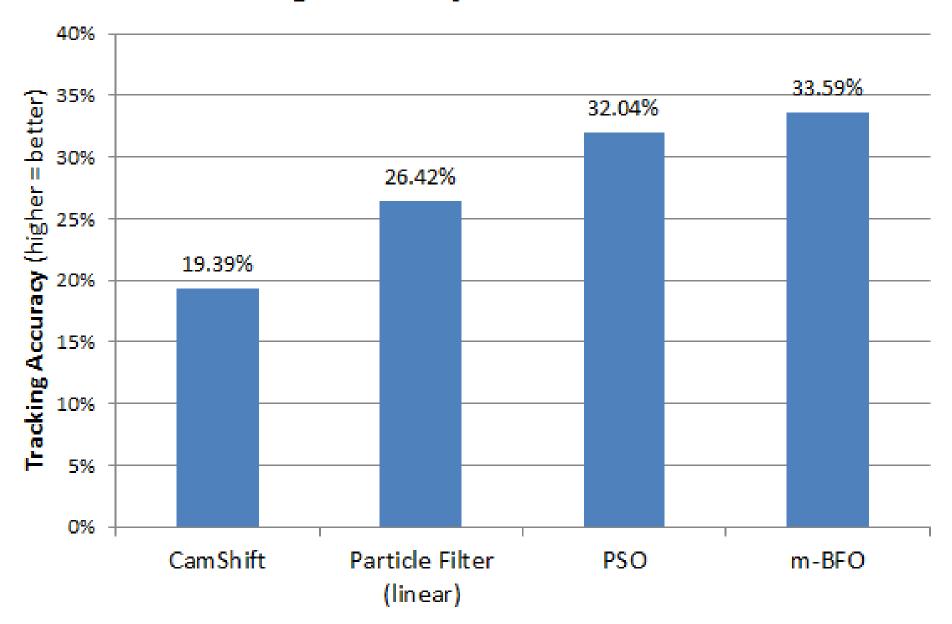




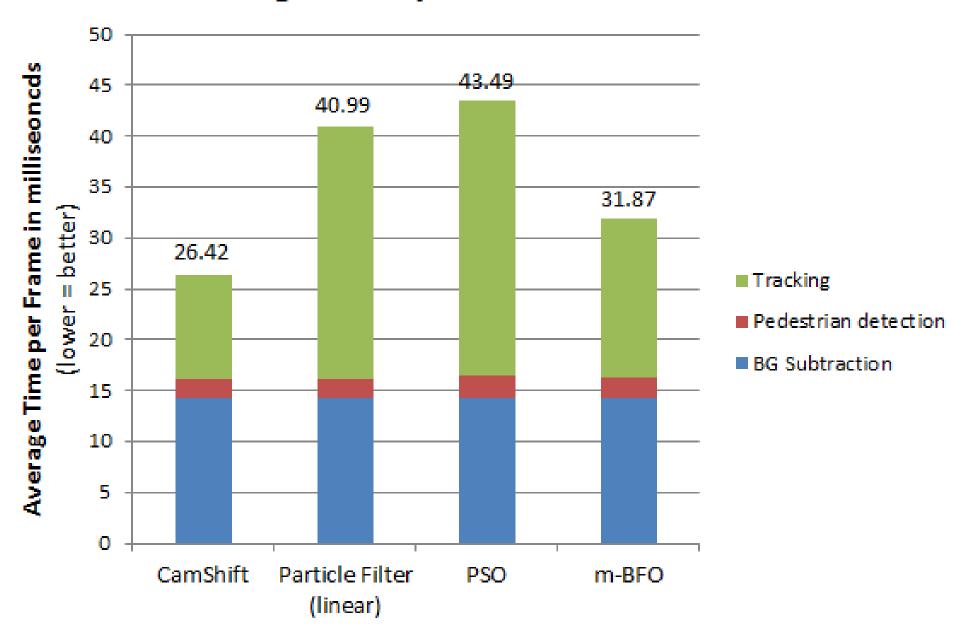


Video	# Frames	# Pedestrians	# ROIs
OneShopOneWait1cor	1,377	6	4,496
OneStopMoveEnter1cor	1,590	19	13,691
ThreePastShop1cor	1,650	8	9,642
ThreePastShop2cor	1,521	9	9,452
TwoEnterShop1cor	1,645	11	7,190
TwoEnterShop2cor	1,605	15	7,930
TwoEnterShop3cor	1,149	14	6,856
Total	10,537	82	59,257

Tracking Accuracy on CAVIAR Videos



Average Time per Frame on CAVIAR



Conclusions

- Criteria: (B) Results are equal to / better than new scientific result
- Best because it helps facilitate real-time tracking systems with an algorithm which improves both accuracy and speed over traditional approaches.