

# Distributed target tracking under realistic network conditions

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[www.eecs.qmul.ac.uk/~andrea/wise-mnet.html](http://www.eecs.qmul.ac.uk/~andrea/wise-mnet.html)

# Context

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- Wireless Sensor Networks (**WSNs**)
  - networks of *autonomous* sensors used for *pervasive* applications
  - large-number deployments, highly scalable
  - resource-constrained
  - scalar data (e.g. temperature, light, pressure)

## The way ahead...

- Wireless Multimedia Sensor Networks (**WMSNs**)
  - vectorial data (e.g. audio, **video**)
  - raw data cannot (always) be transferred
  - local processing is required (but much more complex!)

# Application: multi-sensor tracking

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- Objective

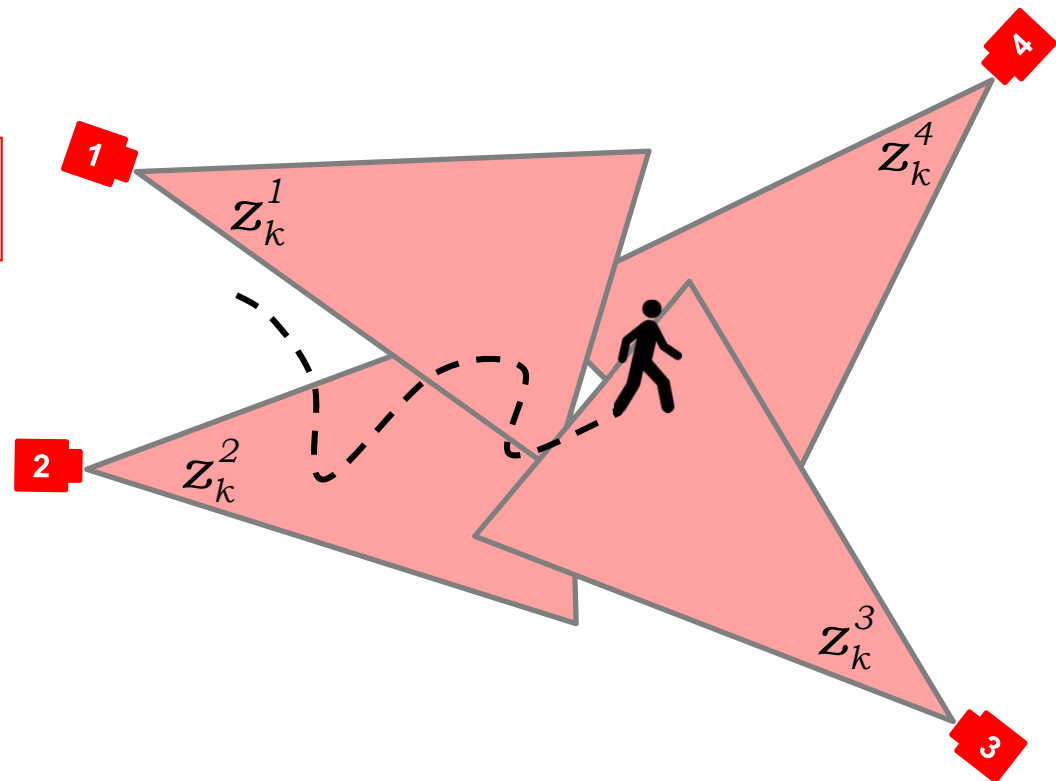
Continuous *estimation* of the target state given a set of *measurements* (observations) obtained from spatially distributed sensing nodes.

$$\mathbf{Z}_k = (z_k^1 \quad z_k^2 \quad \dots \quad z_k^N)$$

Measurements

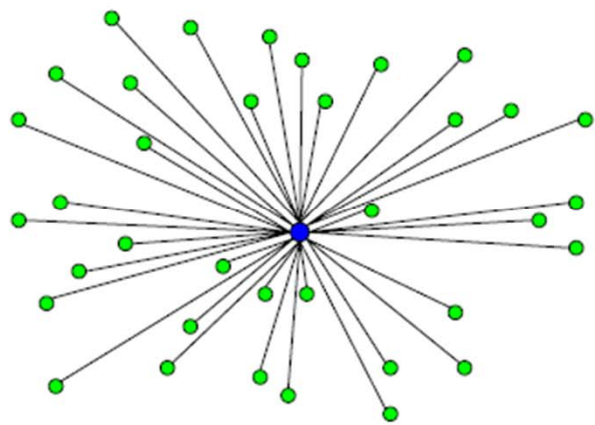
$$x_k = f(\mathbf{Z}_k, \mathbf{Z}_{1:k-1}, x_{0:k-1})$$

State estimation

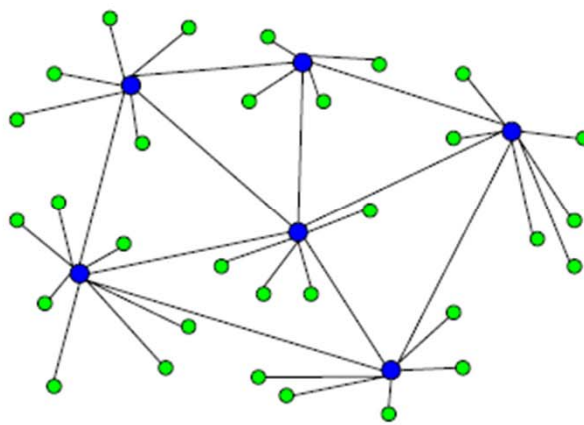


# Approaches

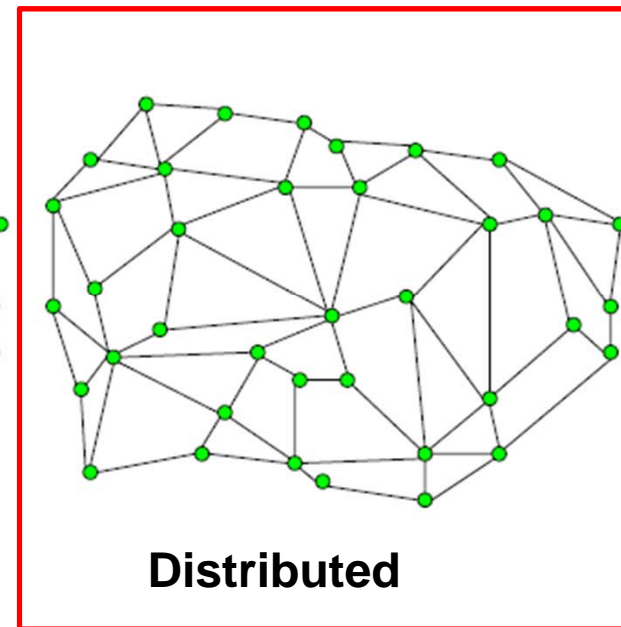
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Centralized



Decentralized



Distributed

## Distributed and decentralized multi-camera tracking

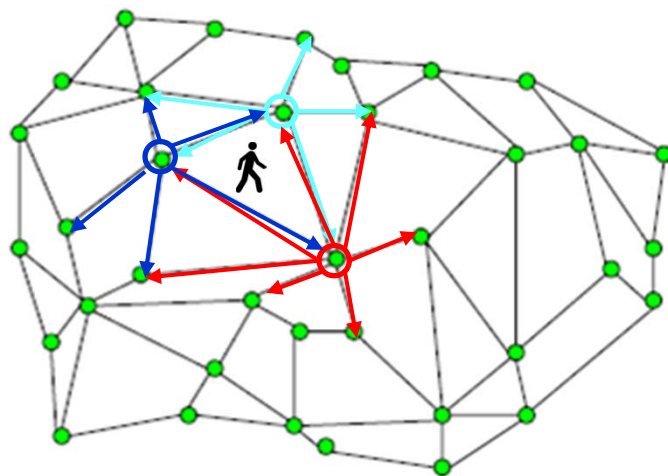
M. Taj, A. Cavallaro

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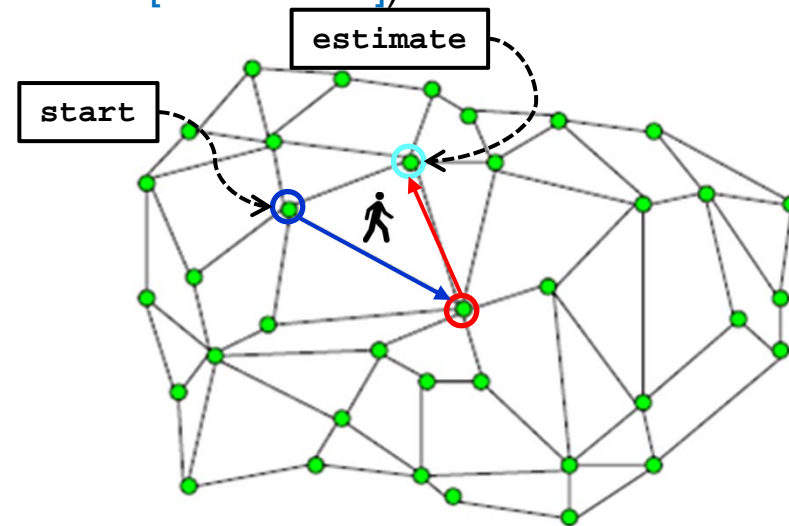
# Distributed tracking: strategies

- Distributed target tracking

- need a collaborative **information exchange** mechanism
- **consensus**-based algorithms
  - Parallel (e.g. Kalman Consensus Filter [Olfati-Saber2005], Distributed Particle Filters [Gu2007])
- data **aggregation** algorithms
  - Sequential (e.g. **Distributed Particle Filters** [Hlinka2009])



consensus



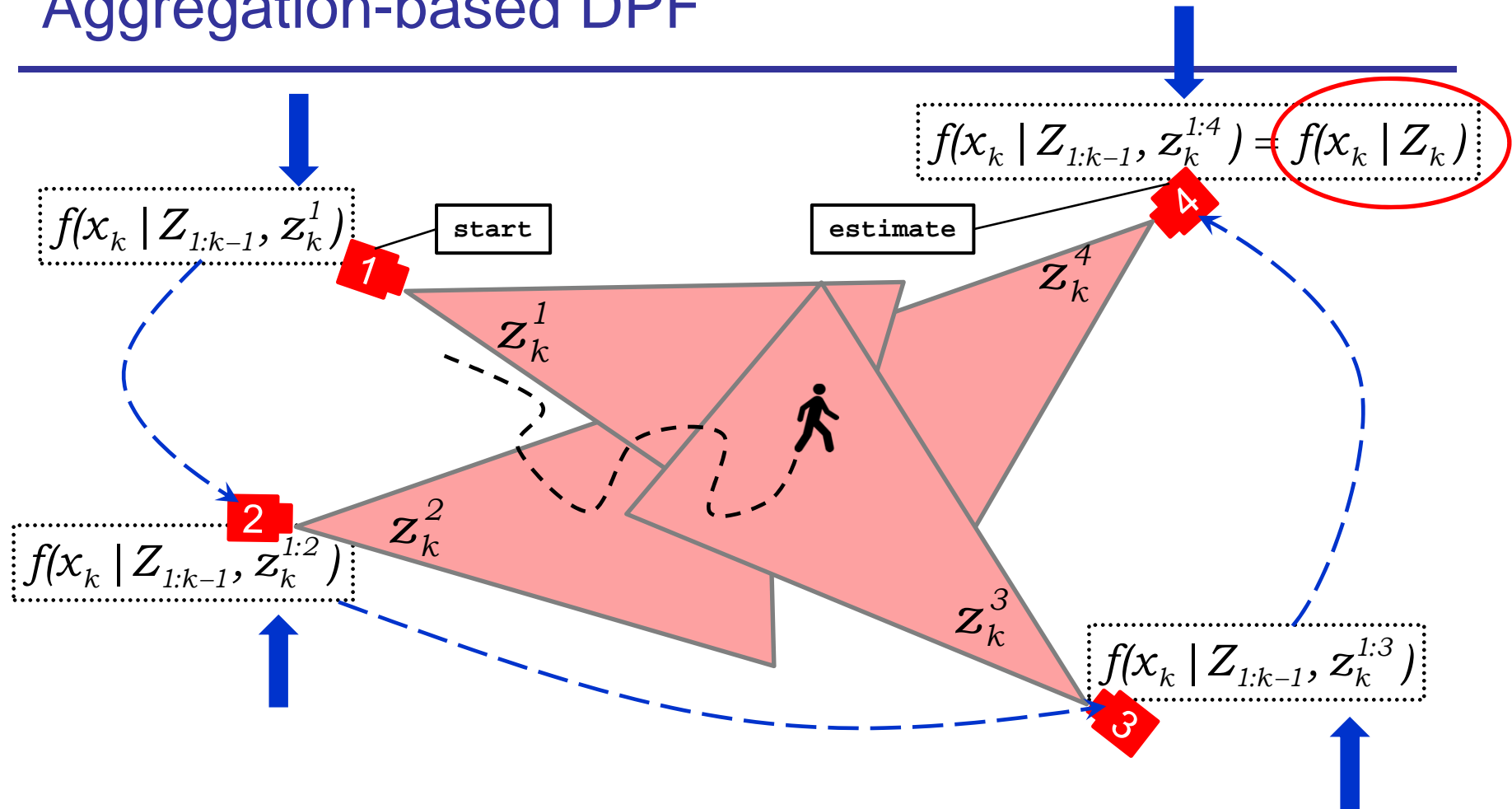
aggregation

# Distributed Particle Filters (DPFs)

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- Basic ideas:
  - each node executes a **local Particle Filter** (PF)
  - measurements are synchronized, calibration is known
  - some information is exchanged
- **Likelihood** sharing [Coates2004]
  - exchange information to have a common model of the likelihood
  - random number generators are synchronized
- **Posterior** sharing
  - the network has a common knowledge of the posterior *pdf*
  - *consensus*-based approach [Sheng2005, Gu2007]
  - **aggregation-based approach** [Sheng2005, Hlinka2009]
    - spatial sequence of aggregation steps
    - Partial Posterior (PP) is exchanged among the nodes

# Aggregation-based DPF



**Problem:** Particle dissemination is not feasible!

**Solution:** Gaussian Mixture Model of the Partial Posterior (GMM-PP)  
Independence from the # of particles

**How to extend this tracking approach  
from WSNs to WMSNs?**

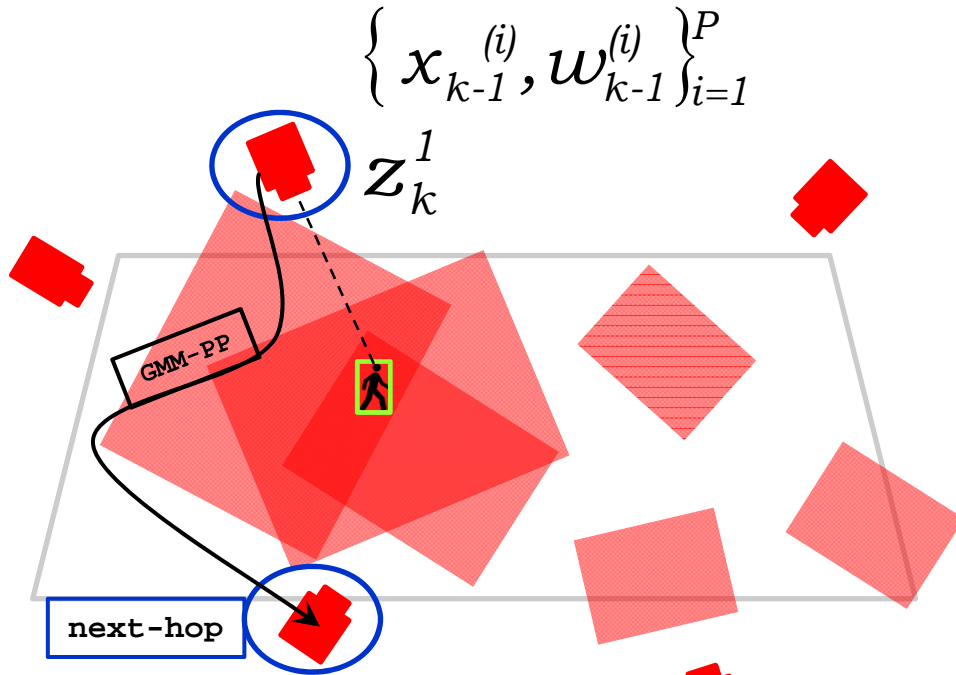


# Proposed approach

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- Objective
  - Distributed tracking under realistic conditions in camera-based **WMSNs**
- Problems
  - existing approaches are theoretical and designed for **WSNs**
  - need adaptation for limited Field-Of-View sensors (cameras)
    - detection miss
    - target hand-over
    - target loss
  - need mechanisms for the definition of the aggregation chain
    - **first node** (starts iteration)
    - **intermediate nodes** (aggregate local measurement to the PP)
    - **last node** (performs estimation)
  - a network-simulator environment is required

# First node



$$\left\{ x_{k-1}^{(i)}, w_{k-1}^{(i)} \right\}_{i=1}^P$$

$$z_k^1$$

next-hop

$$\left\{ \bar{x}_{k-1}^{(i)}, \bar{w}_{k-1}^{(i)} \right\}_{i=1}^P$$

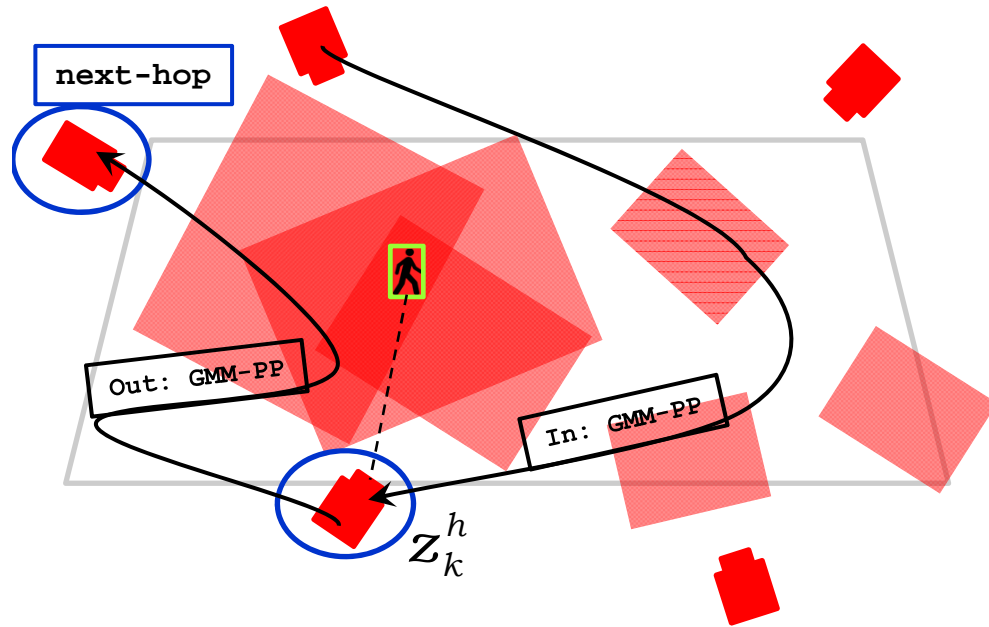
$$x_k^{(i)} \sim f(x_k | \bar{x}_{k-1}^{(i)}) \quad \forall i = 1, \dots, P$$

$$w_k^{(i)} = \frac{f(z_k^1 | x_k^{(i)})}{\sum_{j=1}^P f(z_k^1 | x_k^{(j)})} \quad \forall i = 1, \dots, P$$

1. Knows previous posterior and local measurement
2. Prediction and Update:
  - re-sampling
  - draw from state-transition
  - weight update from likelihood
3. GMM-PP creation
4. Next-hop selection
5. Sends GMM-PP

$$\left\{ x_k^{(i)}, w_k^{(i)} \right\}_{i=1}^P \longrightarrow f_{GMM-PP}^1$$

# Intermediate node $h$



1. Receives PP from node  $h-1$
2. Importance sampling:
  - use the incoming PP as importance function  $g()$
  - draw from importance function
  - weight update: CONDENSATION
3. GMM-PP creation
4. Next-hop selection
5. Sends GMM-PP

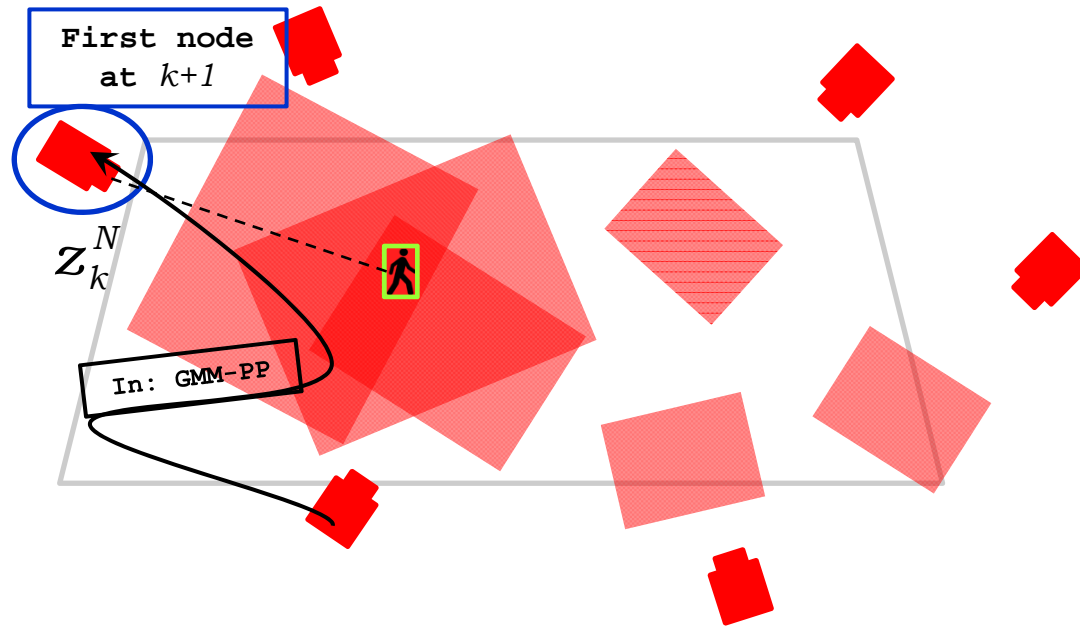
$$g(x_k) = f_{GMM-PP}^{1:h-1}(x_k | z_k^{1:h-1})$$

$$x_k^{(i)} \sim f_{GMM-PP}(x_k | z_k^{1:h-1}) \quad \forall i = 1, \dots, P$$

$$w_k^{(i)} = \frac{f(z_k^h | x_k^{(i)})}{\sum_{j=1}^P f(z_k^h | x_k^{(j)})} \quad \forall i = 1, \dots, P$$

$$\left. \begin{matrix} x_k^{(i)} \sim f_{GMM-PP}(x_k | z_k^{1:h-1}) \\ w_k^{(i)} = \frac{f(z_k^h | x_k^{(i)})}{\sum_{j=1}^P f(z_k^h | x_k^{(j)})} \end{matrix} \right\} \left\{ x_{k-1}^{(i)}, w_{k-1}^{(i)} \right\}_{i=1}^P \longrightarrow f_{GMM-PP}^{1:h}$$

# Last node



1. Receives PP from node  $N-1$
2. Importance sampling as for intermediate nodes
3. Last PP is also the global PP
4. Target state estimation
5. *Next tracking step starts here!*

After importance sampling:  $f_{PP}^{1:N} = f(x_k | Z_k)$

Estimation:  $\hat{x}_k = \sum_{i=1}^P w_k^{(i)} \cdot x_k^{(i)}$

# Experimental setups

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- Simulations
  - number of nodes:  $N = 10, 50, 100, 300, 500, 700, 1000$
  - number of particles:  $P = 100, 300, 500$
  - DPF with different GMM configurations
    - No GMM approximation: *DPF-0*
    - Variable number of GMM components: *DPF-1, DPF-5*
  - realistic network conditions

Simulator: *WiSE-MNet* [www.eecs.qmul.ac.uk/~andrea/wise-mnet.html](http://www.eecs.qmul.ac.uk/~andrea/wise-mnet.html)

# Simulation setup

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- Network
  - T-MAC protocol, BW = 250 kbps
  - request-to-send/clear-to-send mechanism
  - acknowledged-transmission mechanism
  - number of retransmissions: 10
- Cameras
  - Covering 6000 sqm (random uniform distribution)
  - Top-down facing cameras: 6m from the ground plane (FOV is 10m X 6m)
  - Frame rate = 1fps
- 100 simulation runs, each of 10 minutes

# What do we measure?

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- Estimation efficiency

$$E = \frac{K_{tr}}{K}$$

$K_{tr}$  # of estimations (detected events)

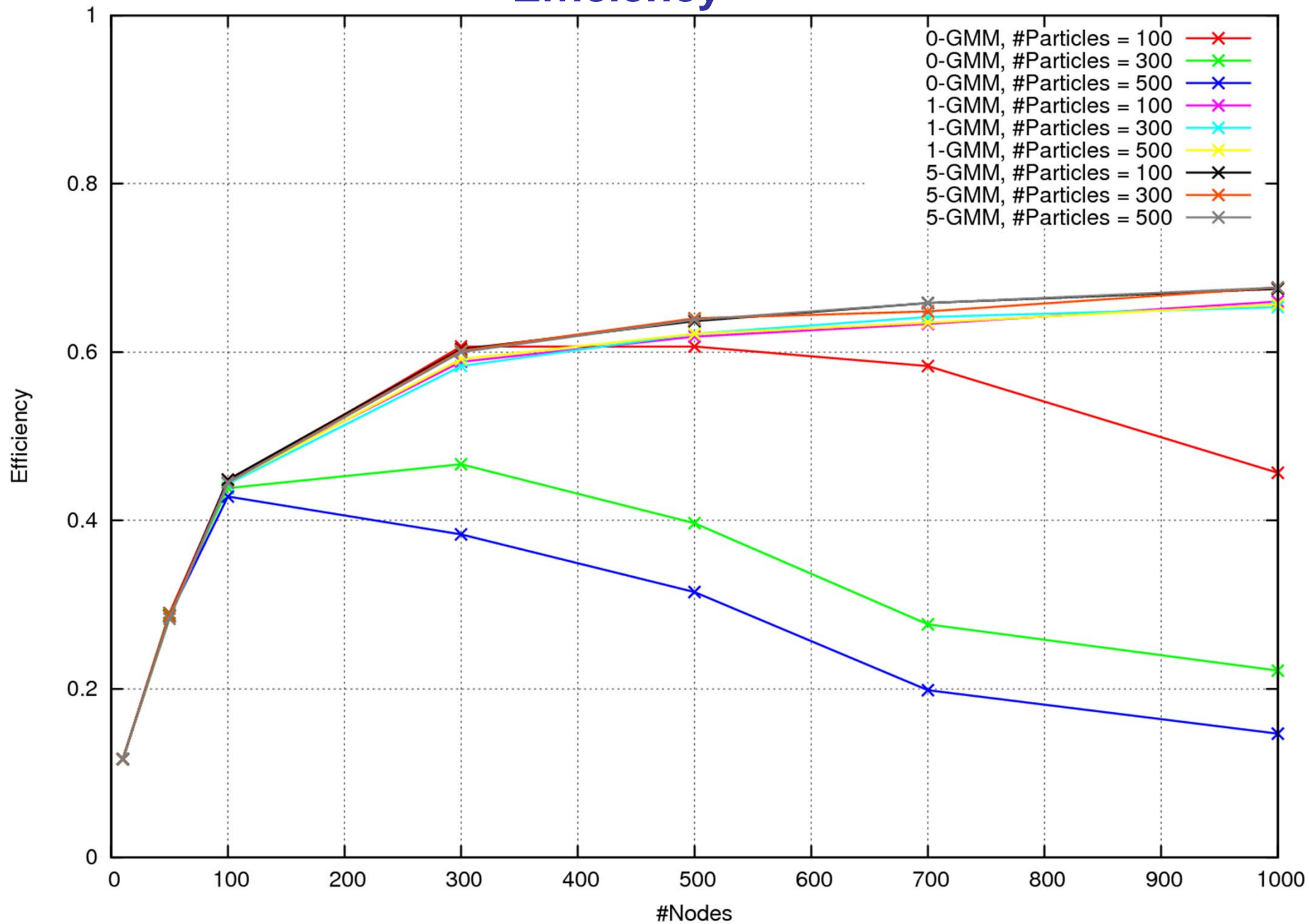
$K$  # of observations (all the events)

- Average estimation delay

$$\bar{D} = \frac{1}{K_{tr}} \sum_{i=1}^{K_{tr}} d(k)$$

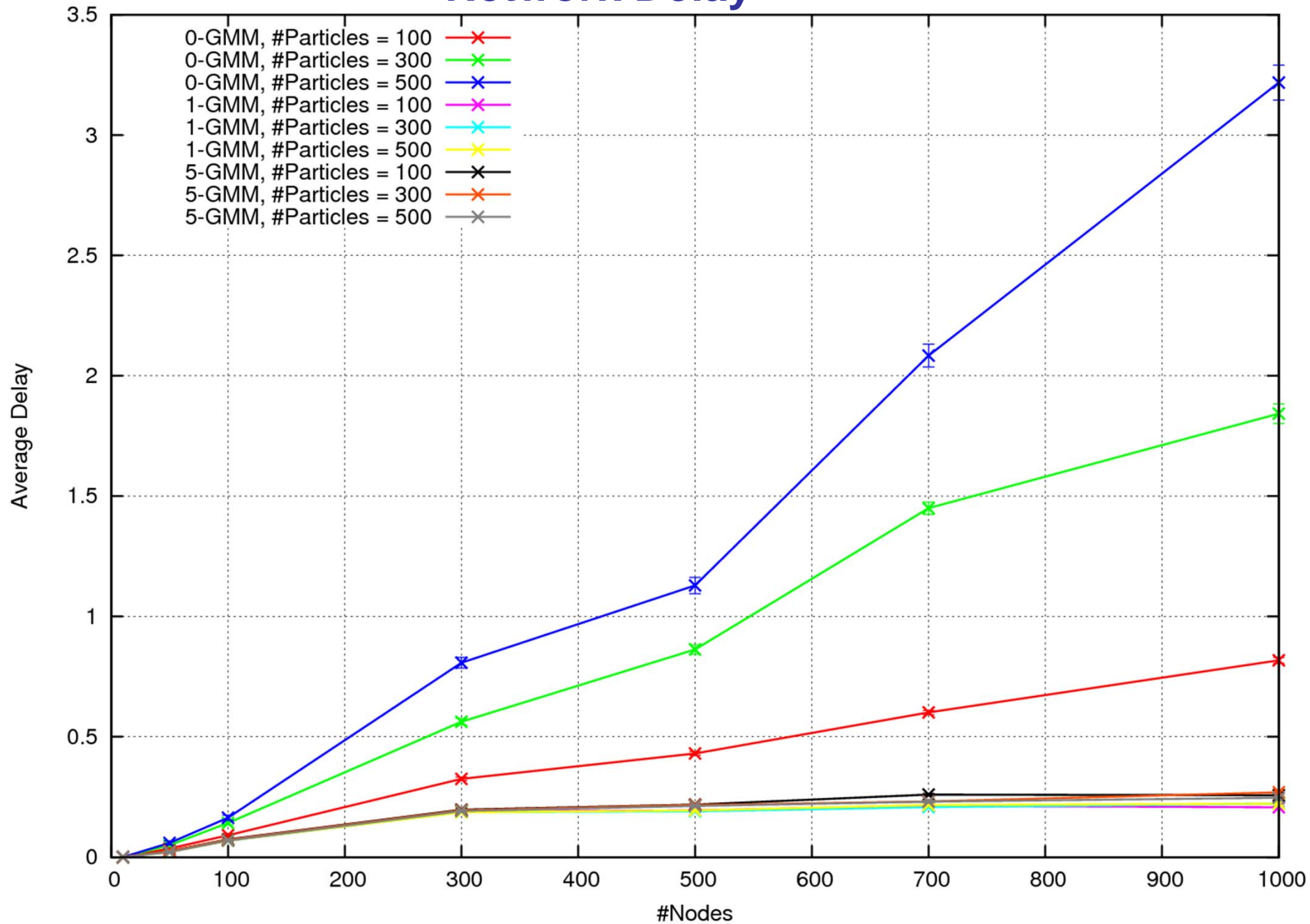
$d(k)$ : Estimation delay for the  $k$ -th tracking step

# Efficiency





# Network Delay



# Conclusions

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- Conclusions
  - distributed target tracking for camera-based WMSNs with a DPF
    - Dealing with limited-FOV sensors
    - Operating on a network-simulator environment
  - importance of co-design between tracking algorithms and communication protocols

Simulator available as open source at  
[www.eecs.qmul.ac.uk/~andrea/wise-mnet.html](http://www.eecs.qmul.ac.uk/~andrea/wise-mnet.html)

- Future work
  - Comparing other state-of-the-art protocols (e.g. consensus-based)
  - Using the full vision-pipeline: more complex features