

# Guaranteed boxed localization in MANETs by interval analysis techniques

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SWIM 08 - 20 June 2008

# Outline

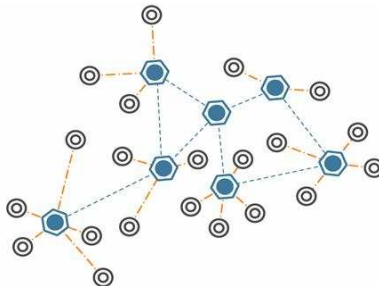
- 1 Introduction
- 2 Model equations
- 3 Monte-Carlo localization
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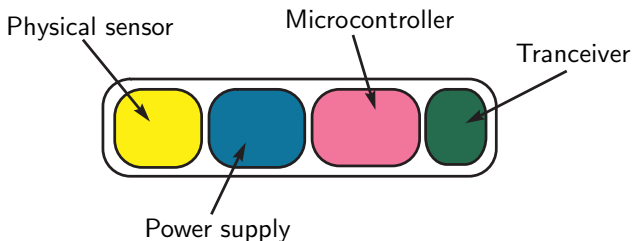
# Definition of MANETs

- MANETs (Mobile Ad hoc sensor NETworks) are networks composed of a **large number** of tiny, cheap and **smart** sensors.



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- Smart sensor



# Applications of MANETs

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- Environment monitoring,
- Video surveillance,
- Military sensing and target tracking,
- Biomedical diagnosis and real-time health monitoring...

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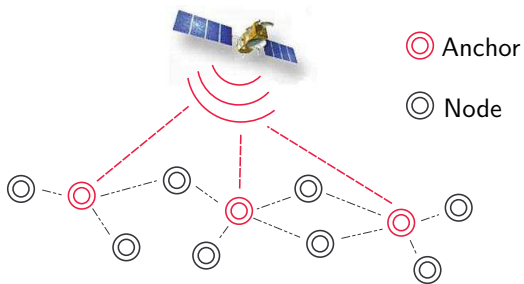


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# Notations and definitions

- **Anchor** - Mobile or fixed sensor equipped with GPS
- **Node** - GPS-less sensor having an unknown position





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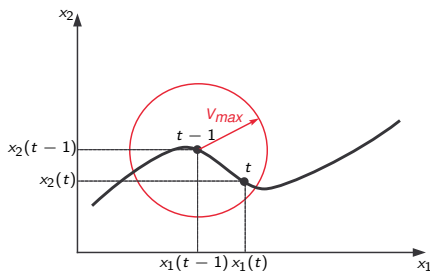
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# Mobility model

## A state space model

The velocity of the mobile nodes is bounded by a maximal value:

$$(x_1(t) - x_1(t-1))^2 + (x_2(t) - x_2(t-1))^2 \leq v_{max}^2$$

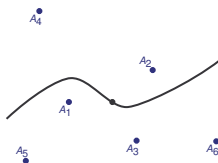


# Observation model

## Connectivity measurements to anchors

Each node receives information from anchors within its sensing range:

$$(x_1(t) - A_{i,1})^2 + (x_2(t) - A_{i,2})^2 \leq r^2, i \in I$$

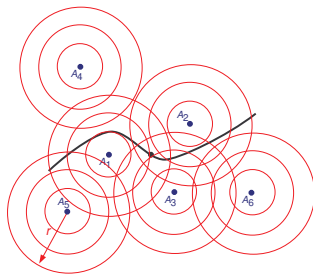


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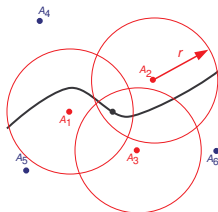


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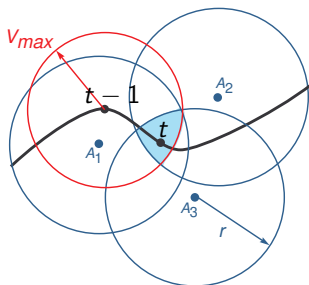
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## Description of the method

- As the particle filter, it generates **particles** to estimate the unknown positions.

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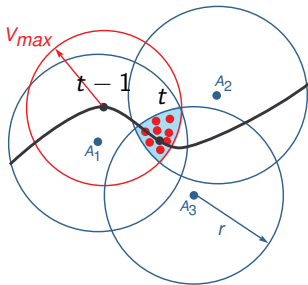
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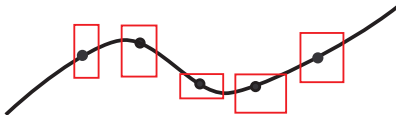


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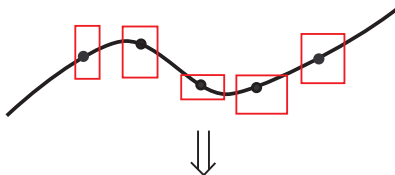
# Definition of the problem

The estimated locations are defined as **position boxes**.



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The localization problem is defined as a **Constraint Satisfaction Problem** in an interval framework.

# Tools

## Constraint Satisfaction Problem

A CSP consists of finding the solution set  $\mathbf{S}$  that satisfies all constraints :

$$\mathbf{S} = \{\mathbf{x} \in \mathbf{D} \mid \mathbf{f}(\mathbf{x}) = 0\}.$$

# Tools

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### **A solution to CSP: Waltz algorithm**

The Waltz contractor propagates repetitively all constraints without any prior order.

# Description of the method

## Two phases :

- 1 Propagation
- 2 Contraction

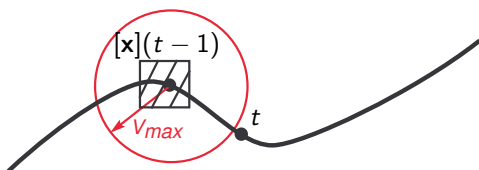


# Propagation phase

## A state space model

The previous solution box is propagated :

$$([x_1](t) - [x_1](t-1))^2 + ([x_2](t) - [x_2](t-1))^2 = [0, v_{max}^2]$$

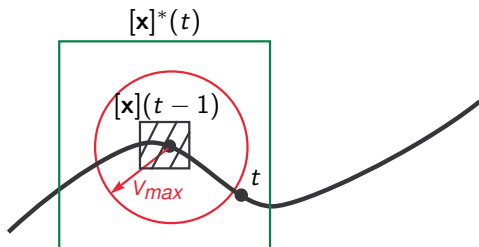


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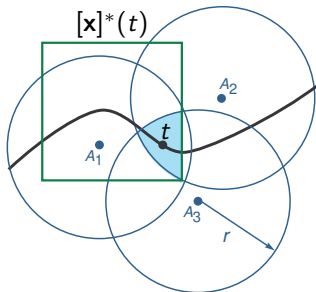


# Contraction phase

## Waltz algorithm using all constraints

The observation model :

$$([x_1](t) - A_{i,1})^2 + ([x_2](t) - A_{i,2})^2 = [0, r^2], i \in I$$

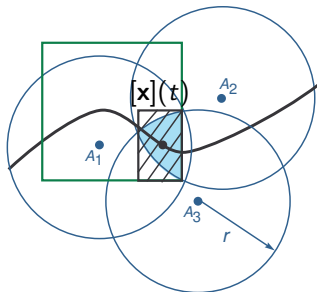


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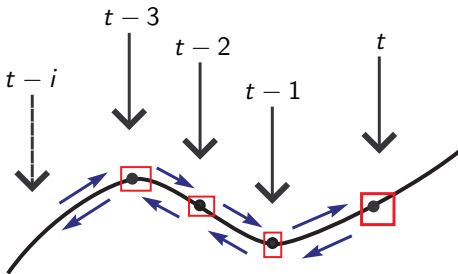
$$([x_1](t) - A_{i,1})^2 + ([x_2](t) - A_{i,2})^2 = [0, r^2], i \in I$$

## Uncertain anchor information

$$([x_1](t) - [A_{i,1}])^2 + ([x_2](t) - [A_{i,2}])^2 = [0, \max[r]^2], i \in I$$

# Back-propagated localization

The boxes are propagated backwardly from and forwardly to the current time-step :

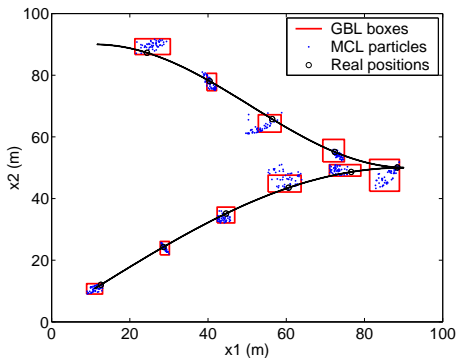


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## Comparison to Monte-Carlo localization

- One mobile node over 100s, 120 anchors, 50 particles

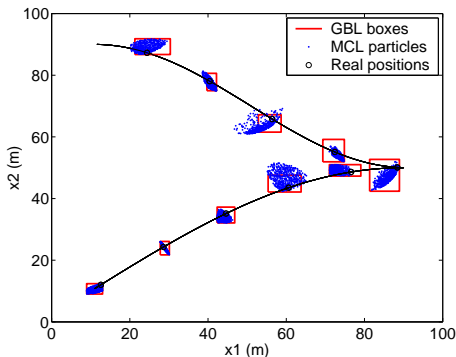


- Computational time - Average error  
 GBL: 0.701s-1.778m; MCL: 2.758s-2.28m



## Comparison to Monte-Carlo localization

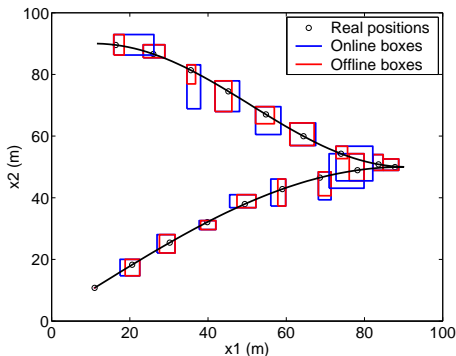
- One mobile node over 100s, 120 anchors, 500 particles



- Computational time - Average error  
 GBL: 0.701s-1.778m; MCL: 29.239s-2.07m

# Back-propagated localization

- Propagation till 6 previous time-steps



- Computational time - Average error  
 Online: 0.765s-1.66m; Offline: 0.893s-1.07m

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- Estimate the distances between nodes and anchors without using the sensing range.

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- Use belief functions to overcome the imperfections of the sensors.

**Thank you**