

# The Degree of Global-State Awareness in Self-Organizing Systems

Christopher Auer, Patrick Wüchner, and Hermann de Meer

University of Passau Department of Computer Science and Mathematics

Theoretical Computer Science Prof. Franz-Josef Brandenburg Computer Networks and Communications Prof. Hermann de Meer

December 10, 2009



## Motivation: Intrusion Detection in Sensor Networks

The Degree of Global-State Awareness

Application to the Sensor Network

Conclusion and Future Work



Table of Contents

# Motivation: Intrusion Detection in Sensor Networks

The Degree of Global-State Awareness

Application to the Sensor Network

Conclusion and Future Work



# 0 0 0 0()0 0 0 0()0 0 0 0 00 0 0 0 00 0 0 0 0



# $\bigcirc \bigcirc \bigcirc \bigcirc \bigcirc$ ()0 0 0 0()0 0 0 0 0 $\mathbf{O}$ $\mathbf{O}$ $\mathbf{O}$ () $\bigcirc \bigcirc \bigcirc \bigcirc \bigcirc \bigcirc \bigcirc$



# $\bigcirc \bigcirc \bigcirc \bigcirc \bigcirc$ ()0 0 0 00 0 0 0 00 0 0 0 00 0 0 0 0



# $\bigcirc \bigcirc \bigcirc \bigcirc \bigcirc$ ()0 0 0 0()()0 0 0 0 0

























### **Motivation: Intrusion Detection in Sensor Networks**









### **Motivation: Intrusion Detection in Sensor Networks**







Using the Phase-Synchronization to Detect Intrusions



Christopher Auer, Patrick Wüchner, and Hermann de Meer | Email: christopher.auer@uni-passau.de Slide 5

### **Motivation: Intrusion Detection in Sensor Networks**



Using the Phase-Synchronization to Detect Intrusions



Christopher Auer, Patrick Wüchner, and Hermann de Meer | Email: christopher.auer@uni-passau.de Slide 5





### **Motivation: Intrusion Detection in Sensor Networks**









### **Motivation: Intrusion Detection in Sensor Networks**





### Motivation: Intrusion Detection in Sensor Networks



Intrusion Detection: Finding a global consensus

- ► > 1/5 of sensor give alarm ⇔ global consensus: Intrusion! (no false-positive)
- Each sensor
  - only observes its immediate neighborhood
  - takes appropriate actions depending on global consensus
- IWSOS 08: Derive appropriate local interaction strategies that use locally accessible information
- However: Is the necessary information distributed?
- How to choose  $\alpha$  and  $\Delta \phi$ ?
- Degree of Global-State Awareness





Table of Contents

## Motivation: Intrusion Detection in Sensor Networks

## The Degree of Global-State Awareness

Application to the Sensor Network

Conclusion and Future Work



- Events occur at discrete time steps  $t \in \mathbb{N}_0$
- Finite set N of entities, each modeled as finite-state automata
- For all  $t \in \mathbb{N}_0$  and  $n \in \mathbf{N}$ :





- Events occur at discrete time steps  $t \in \mathbb{N}_0$
- Finite set N of entities, each modeled as finite-state automata
- For all  $t \in \mathbb{N}_0$  and  $n \in \mathbf{N}$ :
  - ► state s<sub>t,n</sub> and input i<sub>t,n</sub>: local configuration γ<sub>t,n</sub> = (s<sub>t,n</sub>, i<sub>t,n</sub>)





- Events occur at discrete time steps  $t \in \mathbb{N}_0$
- Finite set N of entities, each modeled as finite-state automata
- For all  $t \in \mathbb{N}_0$  and  $n \in \mathbf{N}$ :
  - ► state s<sub>t,n</sub> and input i<sub>t,n</sub>: local configuration γ<sub>t,n</sub> = (s<sub>t,n</sub>, i<sub>t,n</sub>)
  - successor state s<sub>t+1,n</sub> and output o<sub>t,n</sub>





- Events occur at discrete time steps  $t \in \mathbb{N}_0$
- Finite set N of entities, each modeled as finite-state automata
- For all  $t \in \mathbb{N}_0$  and  $n \in \mathbf{N}$ :
  - ► state s<sub>t,n</sub> and input i<sub>t,n</sub>: local configuration γ<sub>t,n</sub> = (s<sub>t,n</sub>, i<sub>t,n</sub>)
  - successor state s<sub>t+1,n</sub> and output o<sub>t,n</sub>
  - Local history  $\overleftarrow{\gamma}_{t,n} = (\gamma_{0,n}, \gamma_{1,n}, \dots, \gamma_{t,n})$





- Events occur at discrete time steps  $t \in \mathbb{N}_0$
- Finite set N of entities, each modeled as finite-state automata
- For all  $t \in \mathbb{N}_0$  and  $n \in \mathbf{N}$ :
  - ► state s<sub>t,n</sub> and input i<sub>t,n</sub>: local configuration γ<sub>t,n</sub> = (s<sub>t,n</sub>, i<sub>t,n</sub>)
  - successor state s<sub>t+1,n</sub> and output o<sub>t,n</sub>
  - Local history  $\overleftarrow{\gamma}_{t,n} = (\gamma_{0,n}, \gamma_{1,n}, \dots, \gamma_{t,n})$
- State space of the system:
- $\blacktriangleright$  Random initial configuration  $\Gamma_0$  with range  $\Gamma_0 \subseteq \Gamma$

► Random local history: 
$$\overleftarrow{\Gamma}_{t,n}$$





Classification Problem

Communication of certain aspects of the system's state at t = 0 to the entities





Classification Problem

- Communication of certain aspects of the system's state at t = 0 to the entities
- Formalization of "aspects of the system's state":
  - Partition of  $\Gamma_0$  into equivalence classes L:

$$\bigcup_{l \in \mathbf{L}} l = \mathbf{\Gamma}_0, \quad \forall l, l' \in \mathbf{L} : l \cap l' = \emptyset, \quad \forall l \in \mathbf{L} : l \neq \emptyset.$$

Random equivalence class L with range L





Classification Problem

- Communication of certain aspects of the system's state at t = 0 to the entities
- Formalization of "aspects of the system's state":
  - Partition of  $\Gamma_0$  into equivalence classes L:

$$\bigcup_{l \in \mathbf{L}} l = \mathbf{\Gamma}_0, \quad \forall l, l' \in \mathbf{L} : l \cap l' = \emptyset, \quad \forall l \in \mathbf{L} : l \neq \emptyset.$$

- Random equivalence class L with range L
- Classification problem L: To which extent is it possible for the system entities' to derive L?





A Very Short Introduction to Shannon's Information Theory

# • Entropy H[X] of random variable X (# $X < \infty$ )





- Entropy H[X] of random variable X (#**X** <  $\infty$ )
- Mean amount of information...
  - ... to specify the outcome of X
  - ... that is provided when the outcome of X is known





- Entropy H[X] of random variable X (#**X** <  $\infty$ )
- Mean amount of information...
  - ... to specify the outcome of X
  - ... that is provided when the outcome of X is known

$$\blacktriangleright X \sim \text{UNI}(\mathbf{X}) \implies \text{H}[X] = \log_2 \# \mathbf{X} \text{ (maximum)}$$



- Entropy H[X] of random variable X (# $X < \infty$ )
- Mean amount of information...
  - ... to specify the outcome of X
  - ... that is provided when the outcome of X is known

$$\triangleright X \sim \text{UNI}(\mathbf{X}) \implies \text{H}[X] = \log_2 \# \mathbf{X} \text{ (maximum)}$$

$$\blacktriangleright X \sim \delta_x(\mathbf{X}) \implies \mathrm{H}[X] = 0 \text{ (minimum)}$$





- Entropy H[X] of random variable X (# $X < \infty$ )
- Mean amount of information...
  - ... to specify the outcome of X
  - ... that is provided when the outcome of X is known
- $\triangleright X \sim \text{UNI}(\mathbf{X}) \implies \text{H}[X] = \log_2 \# \mathbf{X} \text{ (maximum)}$
- $\blacktriangleright X \sim \delta_x(\mathbf{X}) \implies \mathrm{H}[X] = 0 \text{ (minimum)}$
- Measure of uncertainty of a random variable





- Entropy H[X] of random variable X (# $X < \infty$ )
- Mean amount of information...
  - ... to specify the outcome of X
  - ... that is provided when the outcome of X is known
- $\blacktriangleright X \sim \text{UNI}(\mathbf{X}) \implies \text{H}[X] = \log_2 \# \mathbf{X} \text{ (maximum)}$
- $\blacktriangleright X \sim \delta_x(\mathbf{X}) \implies \mathrm{H}[X] = 0 \text{ (minimum)}$
- Measure of uncertainty of a random variable
- Conditional entropy H[X|Y] of X if Y is known:

$$\mathrm{H}[X|Y] = \mathrm{H}[X,Y] - \mathrm{H}[Y].$$





A Very Short Introduction to Shannon's Information Theory

- Entropy H[X] of random variable X (# $X < \infty$ )
- Mean amount of information...
  - ... to specify the outcome of X
  - ... that is provided when the outcome of X is known
- $\blacktriangleright X \sim \text{UNI}(\mathbf{X}) \implies \text{H}[X] = \log_2 \# \mathbf{X} \text{ (maximum)}$
- $\blacktriangleright X \sim \delta_x(\mathbf{X}) \implies \mathrm{H}[X] = 0 \text{ (minimum)}$
- Measure of uncertainty of a random variable
- Conditional entropy H[X|Y] of X if Y is known:

$$\mathrm{H}[X|Y] = \mathrm{H}[X, Y] - \mathrm{H}[Y].$$

 $\blacktriangleright \ 0 \leq \operatorname{H}[X|Y] \leq \operatorname{H}[X]$ 





- Entropy H[X] of random variable X (# $X < \infty$ )
- Mean amount of information...
  - ... to specify the outcome of X
  - ... that is provided when the outcome of X is known
- $\blacktriangleright X \sim \text{UNI}(\mathbf{X}) \implies \text{H}[X] = \log_2 \# \mathbf{X} \text{ (maximum)}$
- $\blacktriangleright X \sim \delta_x(\mathbf{X}) \implies \mathrm{H}[X] = 0 \text{ (minimum)}$
- Measure of uncertainty of a random variable
- Conditional entropy H[X|Y] of X if Y is known:

$$\mathrm{H}[X|Y] = \mathrm{H}[X,Y] - \mathrm{H}[Y].$$

- $\blacktriangleright \ 0 \leq \operatorname{H}[X|Y] \leq \operatorname{H}[X]$
- $H[X|Y] = H[X] \Leftrightarrow X$  and Y are independent





- Entropy H[X] of random variable X ( $\# X < \infty$ )
- Mean amount of information...
  - ... to specify the outcome of X
  - $\blacktriangleright$  ... that is provided when the outcome of X is known
- $\succ X \sim \text{UNI}(\mathbf{X}) \implies \text{H}[X] = \log_2 \# \mathbf{X} \text{ (maximum)}$
- $\triangleright X \sim \delta_x(\mathbf{X}) \implies \operatorname{H}[X] = 0 \text{ (minimum)}$
- Measure of uncertainty of a random variable
- Conditional entropy H[X|Y] of X if Y is known:

$$\mathrm{H}[X|Y] = \mathrm{H}[X,Y] - \mathrm{H}[Y].$$

- $\triangleright$  0 < H[X|Y] < H[X]
- $\blacktriangleright$  H[X|Y] = H[X]  $\Leftrightarrow$  X and Y are independent

$$\blacktriangleright \operatorname{H}[X|Y] = 0 \Leftrightarrow X = f(Y)$$





► To which extent can *L* be derived from entity's  $n \in \mathbf{N}$  local history  $\overleftarrow{\Gamma}_{t,n}$  until time step *t*?





- ► To which extent can *L* be derived from entity's  $n \in \mathbf{N}$  local history  $\overleftarrow{\Gamma}_{t,n}$  until time step *t*?
- Degree of global-state awareness observable at entity n at time step t:

$$\omega_{t,n}(\mathbf{L}) = 1 - \frac{\mathrm{H}[L|\overleftarrow{\Gamma}_{t,n}]}{\mathrm{H}[L]}$$





- ► To which extent can *L* be derived from entity's  $n \in \mathbf{N}$  local history  $\overleftarrow{\Gamma}_{t,n}$  until time step *t*?
- Degree of global-state awareness observable at entity n at time step t:

$$\omega_{t,n}(\mathbf{L}) = 1 - \frac{\mathrm{H}[L]\overleftarrow{\Gamma}_{t,n}]}{\mathrm{H}[L]}$$

►  $\omega_{t,n}(\mathbf{L}) \in [0,1]$ 



 $\cap$ 

 $\cap \cap \cap$ 

The Degree of Global-State Awareness

- ► To which extent can *L* be derived from entity's  $n \in \mathbf{N}$  local history  $\overleftarrow{\Gamma}_{t,n}$  until time step *t*?
- Degree of global-state awareness observable at entity n at time step t:

$$\omega_{t,n}(\mathbf{L}) = 1 - \frac{\mathrm{H}[L]\overleftarrow{\Gamma}_{t,n}]}{\mathrm{H}[L]}$$

$$\omega_{t,n}(\mathbf{L}) \in [0,1]$$
  
 
$$\omega_{t,n}(\mathbf{L}) = 1 \Leftrightarrow L = f(\overleftarrow{\Gamma}_{t,n})$$



 $\cap$ 

 $\cap \cap \cap$ 

The Degree of Global-State Awareness

- ► To which extent can *L* be derived from entity's  $n \in \mathbf{N}$  local history  $\overleftarrow{\Gamma}_{t,n}$  until time step *t*?
- Degree of global-state awareness observable at entity n at time step t:

$$\omega_{t,n}(\mathbf{L}) = 1 - \frac{\mathrm{H}[L]\overleftarrow{\Gamma}_{t,n}]}{\mathrm{H}[L]}$$



- ► To which extent can *L* be derived from entity's  $n \in \mathbf{N}$  local history  $\overleftarrow{\Gamma}_{t,n}$  until time step *t*?
- Degree of global-state awareness observable at entity n at time step t:

$$\omega_{t,n}(\mathbf{L}) = 1 - \frac{\mathrm{H}[L|\overleftarrow{\Gamma}_{t,n}]}{\mathrm{H}[L]}$$

► For the whole system:

$$\omega(\mathsf{L}) = \frac{1}{\#\mathsf{N}} \lim_{t \to \infty} \sum_{n \in \mathsf{N}} \omega_{t,n}(\mathsf{L})$$



Table of Contents

## Motivation: Intrusion Detection in Sensor Networks

The Degree of Global-State Awareness

Application to the Sensor Network

Conclusion and Future Work



Calculation of  $\omega$  for the Sensor Network

- ► Initial configurations  $\Gamma_0$ :  $\phi(0) = 0$  for all sensors, except for the group of sensors with  $\phi(0) = \Delta \phi$  that detected an event
- ▶ Classification problem  $\mathbf{L} = \{l_{\leq 1/5}, l_{>1/5}\}$





Calculation of  $\omega$  for the Sensor Network

- Initial configurations Γ<sub>0</sub>: φ(0) = 0 for all sensors, except for the group of sensors with φ(0) = Δφ that detected an event
- Classification problem  $\mathbf{L} = \{I_{\leq 1/5}, I_{>1/5}\}$
- ► Sensing range: Manhattan distance ≤ 2





Influence of  $\Delta \phi$ 





Influence of  $\Delta \phi$ 





Influence of  $\alpha$ 



• Convergence time is proportional to  $1/\alpha$ 



Influence of  $\alpha$ 



• Convergence time is proportional to  $1/\alpha$ 

 $\blacktriangleright \alpha$  too large: Information about L has no time to spread



Influence of  $\alpha$ 



• Convergence time is proportional to  $1/\alpha$ 

- $\blacktriangleright \alpha$  too large: Information about L has no time to spread
- $\blacktriangleright \ \alpha$  too low: Convergence time too long



VERSITÄT



## Motivation: Intrusion Detection in Sensor Networks

The Degree of Global-State Awareness

Application to the Sensor Network

Conclusion and Future Work

### **Conclusion and Future Work**

Conclusion and Future Work

Christopher Auer, Patrick Wüchner, and Hermann de Meer | Email: christopher.auer@uni-passau.de Slide 17

- Conclusion
  - Entities observe their immediate neighborhood
  - To which extent can the entities derive global-state properties?
  - Degree of Global-State Awareness
  - Intrusion detection in sensor networks
    - Preferable system parameters
    - Influence of convergence time





### **Conclusion and Future Work**

Conclusion and Future Work

- Conclusion
  - Entities observe their immediate neighborhood
  - To which extent can the entities derive global-state properties?
  - Degree of Global-State Awareness
  - Intrusion detection in sensor networks
    - Preferable system parameters
    - Influence of convergence time
- Future Work
  - Application to other application scenarios
  - Formalization of other properties of self-organizing systems
  - Address scalability issues
  - Application to cellular automata



### **Conclusion and Future Work**

Conclusion and Future Work

- Conclusion
  - Entities observe their immediate neighborhood
  - To which extent can the entities derive global-state properties?
  - Degree of Global-State Awareness
  - Intrusion detection in sensor networks
    - Preferable system parameters
    - Influence of convergence time
- Future Work
  - Application to other application scenarios
  - Formalization of other properties of self-organizing systems
  - Address scalability issues
  - Application to cellular automata





