On the Graph Building Problem in Camera Networks

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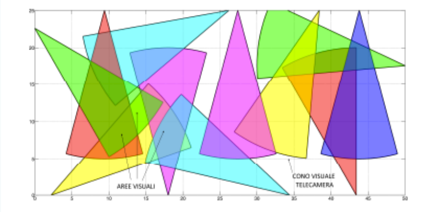
The Graph Building Problem

Distributed scenario:
- The knowledge of the topology of the network by the acting agents is of paramount importance
- Agents share information locally and need to coordinate with neighbors to attain global performance
- Unfeasible manual setup of medium/large scale networks with hundreds of nodes spread across the environment
- Necessity of learning the topology after the network has been deployed

Camera networks: how do the set of camera sensor scenes relate to the environment topology?



Graph description:
- Each node represents a "sensor area"
- Each edge stands for an admissible physical transition from one area to another

Aim:
- Estimate the graph structure in terms of both nodes (i.e. areas of interest) and edges (i.e. the transition probability map) from camera observations, during the system calibration phase

Hidden Markov Model and Baum Welch Algorithm

Assumptions:
- 2D domain and *K* fixed cameras $\{\mathcal{A}_i, i = 1, \ldots, K\}$
- The observation is a binary string: $O_t \in \{0,1\}^K$ entry in the *i*-th position is 1 if the *i*-th camera sees the target object, while it is 0 otherwise
- Different observations imply that the corresponding states of the system are distinguishable

Problem: *given an observation sequence $\mathcal{O}$ infer the set of states $\mathcal{S}$ and the underlying graph $\mathcal{G}$ that constraints their transitions (whose node set is $\mathcal{S}$).*

HMM:
- State set: $\mathcal{S} = \{S_1, S_2, \ldots, S_N\}$
- Observation sequence: $\mathcal{O} = [O_1, \ldots, O_T],\ O_i \in \{v_1, v_2, \ldots, v_M\}, v_i \in \{0,1\}^K$
- State transition probability: $A \in \mathbb{R}^{N\times N}, a_{ij} = \mathbf{P}[q_{t+1} = S_j | q_t = S_i]$
- Observation symbol probability: $B \in \mathbb{R}^{M\times N}, \{b_{ij}\} = \mathbf{P}[O_t = v_i | q_t = S_j]$
- Initial state distribution: $\pi_i = \mathbf{P}[q_1 = S_i]$

➔ Model: $\lambda = (A, B, \pi)$

Problem: *given an initial model λ_0 adjust the model parameters $\{A, B, \pi\}$ to maximize the probability of the observation sequence $\mathcal{O}$ given the model:*

$$\max_\lambda \mathbf{P}[\mathcal{O}|\lambda]$$

Baum-Welch algorithm:
- Expectation-maximization method
- Forward var.: $\alpha_t(i) = \mathbf{P}[O_1, O_2, \ldots, O_t, q_t = S_i|\lambda]$
- Backward var.: $\beta_t(i) = \mathbf{P}[O_{t+1}, \ldots, O_T | q_t = S_i, \lambda]$
- Estimation of the new model: $\{\bar{A}, \bar{B}, \bar{\pi}\}$

$$\mathbf{P}[\mathcal{O}|\bar{\lambda}] \geq \mathbf{P}[\mathcal{O}|\lambda]$$

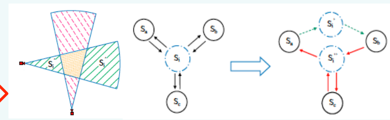
Splitting and HMM Identification

Procedure:
1. An initial topological graph is built directly as a Markov model, in terms of nodes (states) and edges (state transitions)
2. The model is refined through BW algorithm updating the model parameters to better fit the observation sequence
3. The discovery of further states is then carried out by a node splitting procedure, observing the evolution in time of the trajectories

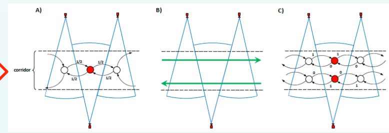
Performance index: *average probability of making the correct prediction for a specific sequence of observations $\mathcal{O}$ of length T based on λ*

$$\eta(\mathcal{O},\lambda) = \sqrt[T]{\prod_{t=0}^{T-1} \mathbf{P}[\hat{y}_{t+1} = y_{t+1}|y_{0:t}]} = \sqrt[T]{\mathbf{P}[\mathcal{O}|\lambda]}$$

Topological splitting: the same observation refers to the target in different positions. Distinct states that relate to the same observation, allows for different future evolution of the trajectory



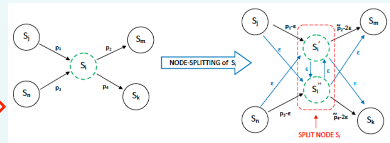
Logical Splitting: past transitions may suggest a preferential direction and allow the estimation of the future state visits (includes topological splitting)



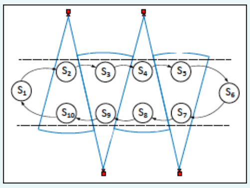
Orthogonality measure:

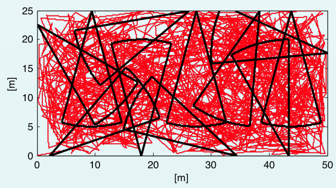
		S_a	S_b (q_{i+1})	S_c
	S_a	0	$\mathbf{P}_{a*b}$	0
q_{i-1}	S_b	$\mathbf{P}_{b*a}$	0	$\mathbf{P}_{b*c}$
	S_c	$\mathbf{P}_{c*a}$	0	$\mathbf{P}_{c*c}$

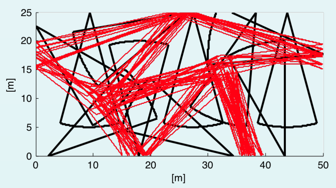
A non-null probability among apparently non related states (i.e. unobserved transitions), is admitted to account for non perfect orthogonality measure and to insert "genetic variability"



Simulations & Discussion







Scenario 1:
- Model of corridor where targets move back and forth at constant speed
- Exhibits the need of both topological splitting and logical splitting
- Beginning: *η=0.5* (same probability of direction change at every step)
- End: *η=1* (prediction capability is perfect)

Scenario 2:
- 2D area with random motion (direction and velocity)
- The splitting procedure does not lead to much improvement (from *η= 0.25* to *η=0.3*): the random walk of the target does not allow good prediction
- It is not possible to predict the future trajectory based on the observation history: depends only on the current observation

Scenario 3:
- 2D area with random motion (direction and velocity) with preferential paths
- Situation in between the corridor-like scenario and the 2D random motion
- Partial exploration but same number of distinct observations as Scenario 2
- Prediction capability improves of about 50%: from *η= 0.3* to *η=0.45*

After each splitting step the performance drops considerably due to the incorrect initialization of the matrix A, however, after a few steps of the Baum-Welch's algorithm, the performance improves becoming higher than before the splitting