Cyber-Physical Systems

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Lecture 16: Spatio-Temporal Reach and Escape Logic











Availability: I can always find a station with at least one bike in a radius of 500 meters

Spread: after 10 time units, there exists a location I' at a certain distance from location I where the number of infected individuals is more than 50





Reliability: we can always find a path of sensors such that all sensors have a battery level greater than 0.5

Spots: regions with low density of protein A are always surrounded by regions with high level of protein B



How to specify such spatio-temporal behaviours in a formal and human-understandable language ?

How to monitor their onset efficiently?

<u>Part 1</u>:

- Space Model and traces
- Spatio- Temporal Reach and Escape Logic (STREL)

<u>Part 2</u>:

- Monitoring
- Applicability to different scenarios





INPUTS

OUTPUTS



Running Example: Wireless Sensor Network



Space Model, Signal and Traces

Spatial Configuration

We consider a discrete space described as a weighted (direct) graph

Reasons:

- many applications, like bike sharing systems, smart grid and sensor networks are naturally framed in a discrete spatial structure
- in many circumstances continuous space is abstracted as a grid or as a mesh, e.g. numerical integration of PDEs

Space Model
$$S = \langle L, W \rangle$$

- L is a set of nodes that we call locations;
- $-W \subseteq L \times \mathbb{R} \times L$ is a proximity function associating a label $w \in \mathbb{R}$ to distinct pair $\ell_1, \ell_2 \in L$. If $(\ell_1, w, \ell_2) \in W$, it means that there is an edge from ℓ_1 to ℓ_2 with weight $w \in \mathbb{R}$



Example





Route
$$\tau = \ell_0 \ell_1 \ell_2 \dots$$

It is a infinite sequence s.t. $\forall i \ge 0 \exists w s.t. (\ell_i, w, \ell_{i+1}) \in W$



 $\ell_0 \ell_1 \ell_2 \ell_1 \dots$ is a route

 $\ell_0\ell_1\ell_2\ell_3$... is a not route

 $\tau[i]$ to denote the i - th node τ $\tau(\ell)$ to denote the first occurrence of $\ell \in \tau$

Route Distance
$$d^f_{ au}[i]$$

The distance $d_{\tau}^{f}[i]$ up to index *i* is:

$$d_{\tau}^{f}[i] = \begin{cases} 0 & i = 0\\ f(d_{\tau[1..]}^{f}[i-1], w) & (i > 0) \text{ and } \tau[0] \stackrel{w}{\mapsto} \tau[1] \end{cases}$$

$$d^f_{\tau}(\ell) = d^f_{\tau}[\tau(\ell)]$$

Route Distance
$$d_{\tau}^{f}[i]$$



weight(x, y) = x + y

hops(x, y) = x + 1

$$\begin{aligned} d_{\ell_0\ell_1\ell_2..}^{weight}[2] &= \text{weight}(d_{\ell_1\ell_2..}^{weight}[1], 4) = d_{\ell_1\ell_2}^{weight}[1] + 4 = ... \\ &= \text{weight}(d_{\ell_2..}^{weight}[0], 2) + 4 = 6 \end{aligned}$$

Location Distance
$$d_S^f[\ell_i, \ell_j]$$

$$d_{S}^{f}[\ell_{i}, \ell_{j}] = \min\{d_{\tau}[\ell_{j}] | \tau \in Routes(S, \ell_{i})\}$$



$$d_S^{hops}[\ell_0, \ell_2] = \mathbf{2}$$

Location Distance

$$d_{S}^{f}[\ell_{i}, \ell_{j}] = \min\{d_{\tau}[\ell_{j}] | \tau \in Routes(S, \ell_{i})\}$$



$$d_S^{hops}[\ell_0,\ell_2]$$
 = 1

Signal and Trace

Spatio-Temporal Signals $\sigma: L \to \mathbb{T} \to D$

Spatio-Temporal Trace $\vec{x}: L \to \mathbb{T} \to D^n$

$$\begin{aligned} x(\ell) &= (\nu_B, \nu_T) \\ x(\ell, t) &= (\nu_B(t), \nu_T(t)) \end{aligned}$$

Dynamic Spatial Model

$$(t_i, S_i)$$
 for $i = 1, ..., n$ and $S(t) = S_i \forall t \in [t_i, t_{i+1})$







Spatio-Temporal Reach and Escape Logic (STREL)

It is an extension of the Signal Temporal Logic with a number of spatial modal operators

STREL Syntax $\varphi \coloneqq true \mid \mu \mid \neg \varphi \mid \varphi_1 \land \varphi_2 \mid \varphi_1 \sqcup_I \varphi_2 \mid \varphi_1 \operatorname{S}_I \varphi_2 \mid \varphi_1 \mathcal{R}_d^f \varphi_2 \mid \mathcal{E}_d^f \varphi$

In addition, we can derive:

- The disjunction operator: V
- the temporal operators: F_I , G_I , O_I , H_I
- the spatial operators: somewhere, everywhere and surround



Reach:
$$\varphi_1 \mathcal{R}^f_{[d_1,d_2]} \varphi_2$$

 (S, \vec{x}, ℓ, t) satisfies $\varphi_1 \mathcal{R}^f_{[d_1, d_2]} \varphi_2$ iff it satisfies φ_2 in a location ℓ' reachable from ℓ through a route τ , with a length $d^f_{\tau}(\ell') \in [d_1, d_2]$ and such that $\tau[0] = \ell$ and all its elements with index less than $\tau(\ell')$ satisfy φ_1



Escape:
$$\mathcal{E}^f_{[d_1,d_2]} arphi$$

 (S, \vec{x}, ℓ, t) satisfies $\mathcal{E}_{[d_1, d_2]}^f \varphi$ if and only there exists a route τ and a location $\ell' \in \tau$ such that $\tau[0] = \ell, d_S^f[\ell, \ell'] \in [d_1, d_2]$ and all elements $\tau[0], ..., \tau[k]$ (with $\tau(l') = k$) satisfy φ

Escape:
$$\mathcal{E}^{hops}_{[3,\infty]}$$
orange



$$\tau = \ell_{9}\ell_{10}\ell_{11}\ell_{12}$$

$$\tau[0] = \ell_{9}, \ \tau[3] = \ell_{12}$$

$$d_{S}^{hops}[\ell_{9}, \ell_{12}] = 3$$

Somewhere:

 $\otimes^{J}_{\left[d_{1},d_{2}\right]} \varphi$



 (S, \vec{x}, ℓ, t) satisfies $\bigotimes_{[d_1, d_2]}^{f} \varphi$ iff there exists a location ℓ' reachable from ℓ , and a s.t. $d_S^f[\ell, \ell'] \in [d_1, d_2]$, that satisfies φ

 $\otimes^{hops}_{[3,5]} pink$

 $\tau[0] = \ell_1, \, \tau[k] = \ell_{35}$ $\tau = \ell_1 \dots \ell_{35}$

 $d_{\tau}^{hops}(k) \in [3,5]$



Surround:
$$arphi_1 igotimes_{\left[d_1,d_2
ight]}^f arphi_2$$

 (S, \vec{x}, ℓ, t) iff there exists a φ_1 -region that contains ℓ , all locations in that region satisfies φ_1 and are reachable from ℓ via a path with length less than d_2 .

All the locations that do not belong to the φ_1 -region but are directly connected to a location of that region must satisfy φ_2 and be reached from ℓ via a path with length in the interval $[d_1, d_2]$.

Surround: $green \otimes_{[0,100]}^{hops} blue$







Offline Monitoring Algorithm

Spatial Boolean Signal

 $s_{\varphi}: L \rightarrow [0, T] \rightarrow \{0, 1\}$ such that $s_{\varphi}(\ell, t) = 1 \Leftrightarrow (S, \vec{x}, \ell, t) \vDash \varphi$



Offline Monitoring Algorithm

Spatial Quantitative Signal

 $\rho_{\varphi}: L \to [0, T] \to \mathbb{R} \cup \pm \infty \quad \text{such that} \quad \rho_{\varphi}(\ell, t) = \rho(\mathcal{S}, \vec{x}, \ell, t)$



INPUTS

OUTPUTS



Offline Monitoring Algorithm



Spatial Boolean satisfaction Spatial Quant. satisfaction

Spatial Boolean signals Spatial Quant. signals

Secondary signals

Primary signals

Computational consideration

- Temporal operators: like in STL monitoring [1] is **linear** in the length of the signal times the number of locations in the spatial model.
- Spatial properties are more expensive, they are based on a variations of the classical Floyd-Warshall algorithm. The number of operations to perform is quadratic for the reach operator and cubic for the escape

Static Space and Regular Grid

The formation of Patterns



Space model: a K×K grid treated as a graph, $cell(i, j) \in L = \{1, ..., K\} \times \{1, ..., K\}$

Spatio-Temporal Trajectory: $x: L \to \mathbb{T} \to \mathbb{R}^2$ s.t. $x(\ell) = (x_A, x_B)$

Spot formation property

$$\phi_{spot_{form}} = F_{[19,20]}G((A \le 0.5) \otimes_{[1,w_2]}^{hops} (A > 0.5))$$









 $x_A(50,\ell)$

Boolean sat.

Quantitative sat.

$$\phi_{\textit{pattern}} := \square^{\textit{hops}} \otimes^{\textit{hops}}_{\lceil 0 \ 15 \rceil} \phi_{\textit{spot}_{\textit{form}}}$$





Static Space and Stochastic Systems

Application to Stochastic Systems

STREL can be applied on stochastic systems considering methodologies as Statistical Model Checking (SMC)

Stochastic process $M = (T, A, \mu)$ where T is a trajectory space and μ is a probability measure on a σ -algebra of T

We approximate the satisfaction probability $S(\varphi, t)$, i.e. the probability that a trajectory generated by the stochastic process \mathcal{M} satisfies the formula φ .

We can do something similar with the quantitative semantics computing the robustness distribution



Bike Sharing Systems (BSS)

London Santander Cycles Hire network



- 733 bike stations (each with 20-40 slots)
- a total population of 57,713 agents (users) picking up and returning bikes

We model it as a Population Continuous Time Markov Chain (PCTMC) with timedependent rates, using historic journey and bike availability data.

Prediction for 40 minutes.

Bike Sharing Systems (BSS)

Spatio-Temporal Trajectory: $x: L \to \mathbb{T} \to \mathbb{Z}^2$ s.t. $x(i, t) = (B_i(t), S_i(t))$

Space model

- Locations: $L = \{bike \ stations\},\$
- Edges: $(\ell_i, w, \ell_j) \in W$ iff $w = || \ell_i \ell_j || < 1$ kilometer



std in [0, 0.0158] , mean std = 0.0053.

std in [0, 0.0158] , mean std = 0.0039.

Availability of Bikes $\phi_1 = G\{ \bigotimes_{[0,d]}^{weight}(B > 0) \land \bigotimes_{[0,d]}^{weight}(S > 0) \}$

d = 300 m

Latitude



std in [0, 0.0151], mean std = 0.0015.

d = 600m

Availability of Bikes $\phi_1 = G\{ \bigotimes_{[0,d]}^{weight}(B > 0) \land \bigotimes_{[0,d]}^{weight}(S > 0) \}$

Satisfaction probability of some BBS stations vs distance d=[0,1.0]



Bike Sharing Systems (BSS)

$$\psi_1 = \mathcal{G}\left\{ \bigotimes_{[0,d]}^{weight} \left(\mathcal{F}_{[t_w,t_w]} B > 0 \right) \land \bigotimes_{[0,d]}^{weight} \left(\mathcal{F}_{[t_w,t_w]} S > 0 \right) \right\}$$

Average walking speed of 6.0 km/h, e.g. d = 0.5 km -> t_w = 6 minutes

The results similar to the results of previous property

Dynamic Space



Mobile Ad-hoc sensor NETwork (MANET)



Mobile Ad-hoc sensor NETwork (MANET)

Space model S(t)

- Locations: $L = \{ devices \},\$
- Edges: $(\ell_i, w, \ell_j) \in W$ iff $w = || \ell_i \ell_j || < \min(r_i, r_j)$

Spatio-Temporal Trajectory: $x: L \to \mathbb{T} \to \mathbb{Z} \times \mathbb{R}^2$ s.t. x(i,t) = (nodeType, battery, temperature)nodeType = 1, 2, 3 for coordinator, rooter, and end_device

Connectivity in a MANET

"an end device is either connected to the coordinator or can reach it via a chain of routers"

"broken connection is restored within h time units"

Connectivity in a MANET

"an end device is either connected to the coordinator or can reach it via a chain of routers"

$$\phi_{connect} = device \mathcal{R}^{hop}_{[0,1]}(router \mathcal{R}^{hop}coord)$$

"broken connection is restored within h time units"

$$\phi_{connect_restore} = \mathbf{G}(\neg \phi_{connect} \rightarrow \mathbf{F}_{[0,h]} \phi_{connect})$$

Boolean Satisfaction at each time step

$$\phi_{connect} = device \mathcal{R}_{[0,1]}^{hop}(router \mathcal{R}^{hop}coord)$$



Delivery in a MANET

"from a given location, we can find a path of (hops) length at least 5 such that all nodes along the path have a battery level greater than 0.5"

$$\psi_3 = \mathcal{E}^{hops}_{[5,\infty]}(battery > 0.5)$$

Reliability in a MANET

"reliability in terms of battery levels, e.g. battery level above 0.5

$$\phi_{reliable_router} = ((battery > 0.5) \land router) \mathcal{R}^{hop} coord$$

$$\phi_{reliable_connect} = device \mathcal{R}_{[0,1]}^{hop}(\phi_{reliable_router})$$

Moonlight: https://github.com/MoonLightSuite/MoonLight/wiki

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🖟 MoonLig	htSuite / Moo	onLight								 Watch 	7	☆ Star	4	앟 Fork	1
<> Code	! Issues 2	ຳ Pull requests	Actions	III Project	ts 1 🗰 V	Viki	Security	Insights							

Home

Simone edited this page on 1 Jul · 30 revisions

MoonLight [build passing] (codecov 39%)	Pages			
MoonLight is a light-weight Java-tool for monitoring temporal, spatial and spatio-temporal properties of distributed complex systems, as Cyber-Physical Systems and Collective Adaptive Systems.	Moonlight Script Syntax			
It supports the specification of properties written with the <i>Reach and Escape Logic</i> (STREL). STREL is a linear-time temporal logic, in particular, it extends the <i>Signal Temporal Logic</i> (STL) with a number of spatial operators that permit to described complex spatial behaviors as being surround, reaching target locations, and escaping from specific regions.	Installation Getting Started Python			
MoonLightis implemented in Java, but it features also a MATLAB interface that allows the monitoring of spatio-temporal signals generated within the MATLAB framework. A Python Interface is under development.	Clone this wiki locally			
Getting Started	https://github.com/Moor	Ľ		
First, you need to download JAVA (version 8) and set the environmental variable				
JAVA_HOME= path to JAVA home directory				

Then you need to get or generate the executable for Python or MATLAB.

First, you need to clone our repository

\$ git clone https://github.com/MoonLightSuite/MoonLight.git

or download it (link).

Then you need to compile it by executing the following Gradle tasks in the console

```
(atomicExpression)
             ! Formula
2
             Formula & Formula
3
            Formula | Formula
4
            Formula -> Formula
5
            Formula until [a b] Formula
6
            Formula since [a b] Formula
7
            eventually [a b] Formula
8
             globally [a b] Formula
9
             once [a b] Formula
10
            historically [a b] Formula
11
             escape(distanceExpression)[a b] Formula
12
             Formula reach (distanceExpression)[a b] Formula
13
             somewhere(distanceExpression) [a b] Formula
14
             everywhere (distanceExpression) [a b] Formula
15
            {Formula}
16
```

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