Complex Event Recognition under Uncertainty

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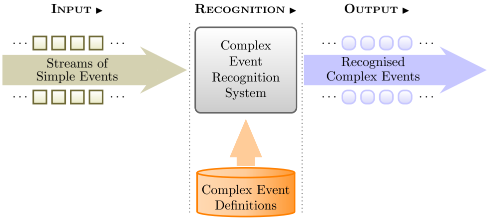
https://cer.iit.demokritos.gr

Complex Event Recognition (Event Pattern Matching)*,†,‡



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†Artikis et al, Dagstuhl Seminar on the Foundations of Composite Event Recognition. SIGMOD Record, 2020.

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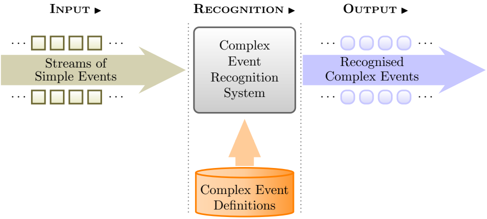
Complex Event Recognition (Event Pattern Matching)[*,†,‡]



https://cer.iit.demokritos.gr (maritime-recognition)

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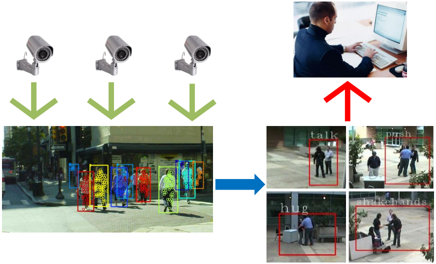
Human Activity Recognition



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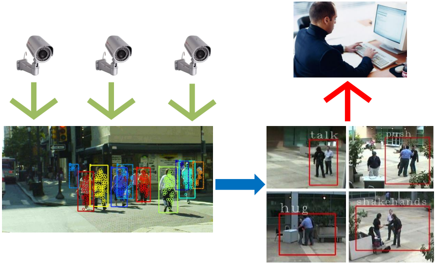

https://cer.iit.demokritos.gr (activity recognition)

Event Calculus*

- A logic programming language for representing and reasoning about events and their effects.
- Key components:
  - event (typically instantaneous).
  - fluent: a property that may have different values at different points in time.

* Kowalski and Sergot, A Logic-based Calculus of Events. New Generation Computing, 1986.

Event Calculus*

- A logic programming language for representing and reasoning about events and their effects.
- Key components:
  - event (typically instantaneous).
  - fluent: a property that may have different values at different points in time.
- Built-in representation of inertia:
  - $F = V$ holds at a particular time-point if $F = V$ has been *initiated* by an event at some earlier time-point, and not *terminated* by another event in the meantime.

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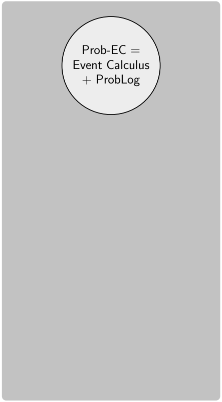
Online Probabilistic Interval-Based Event Calculus



Online Probabilistic Interval-Based Event Calculus

Prob-EC = Event Calculus + ProbLog

Event Calculus Axioms

holdsAt$(F = V, T)$ $\leftarrow$
  initially$(F = V)$,
  not broken$(F = V, 0, T)$.

holdsAt$(F = V, T)$ $\leftarrow$
  initiatedAt$(F = V, T_s)$, $T_s < T$,
  not broken$(F = V, T_s, T)$.

$\vdots$

Online Probabilistic Interval-Based Event Calculus

Application-Specific Rules

$\mathsf{initiatedAt}(moving(P_1, P_2) = \mathsf{true},\ T) \leftarrow$
$\quad \mathsf{happensAt}(walking(P_1),\ T),$
$\quad \mathsf{happensAt}(walking(P_2),\ T),$
$\quad \mathsf{holdsAt}(close(P_1, P_2) = \mathsf{true},\ T),$
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$\mathsf{terminatedAt}(moving(P_1, P_2) = \mathsf{true},\ T) \leftarrow$
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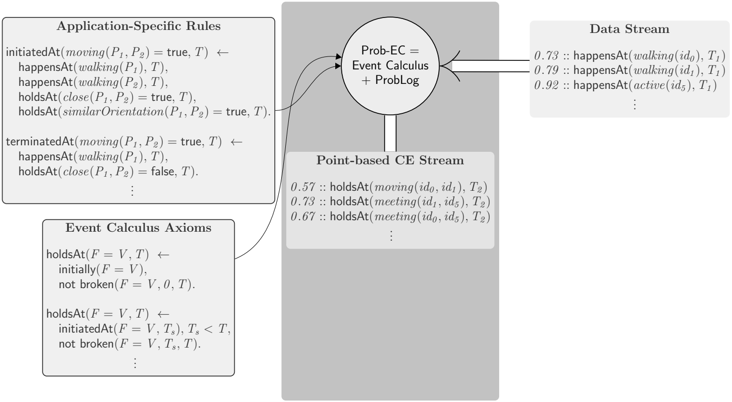
Data Stream

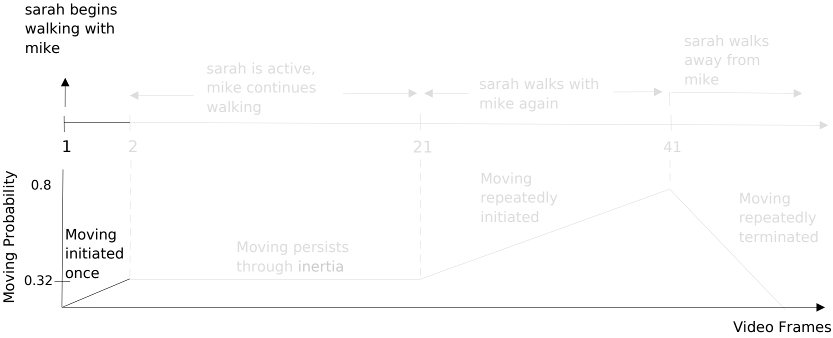
0.73 :: happensAt($walking(id_0)$, T_1)
0.79 :: happensAt($walking(id_1)$, T_1)
0.92 :: happensAt($active(id_5)$, T_1)

$\vdots$

Online Probabilistic Interval-Based Event Calculus



Instantaneous Recognition



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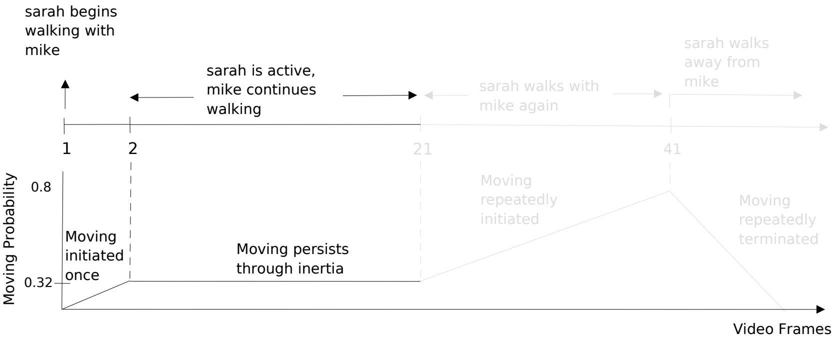
\end{aligned}$$

$$0.70 :: \textbf{happensAt}(\mathit{walking}(\mathit{mike}),\ 1).$$
$$0.46 :: \textbf{happensAt}(\mathit{walking}(\mathit{sarah}),\ 1).$$

Instantaneous Recognition



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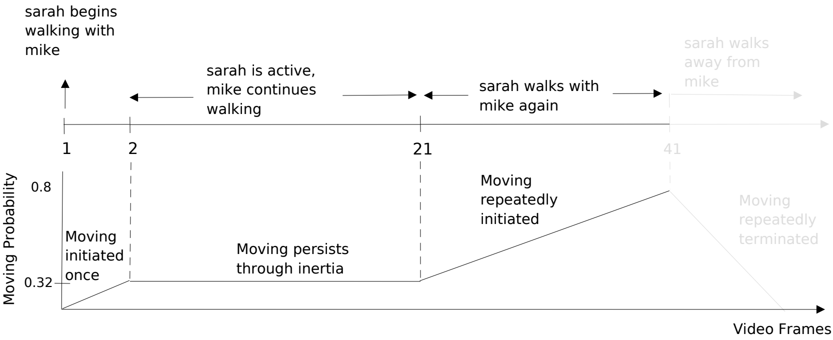

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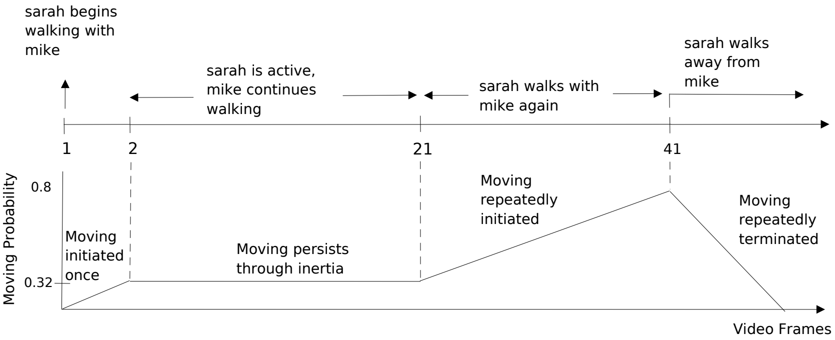
Instantaneous Recognition



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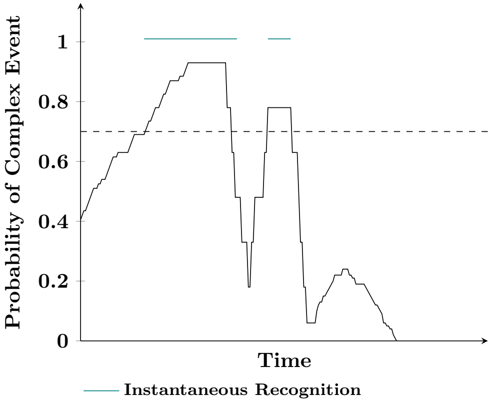
$0.82 :: \textbf{happensAt}(\mathit{inactive}(\mathit{mike}),\ 41).$

$0.79 :: \textbf{happensAt}(\mathit{walking}(\mathit{sarah}),\ 41).\ \cdots$

Instantaneous Recognition*



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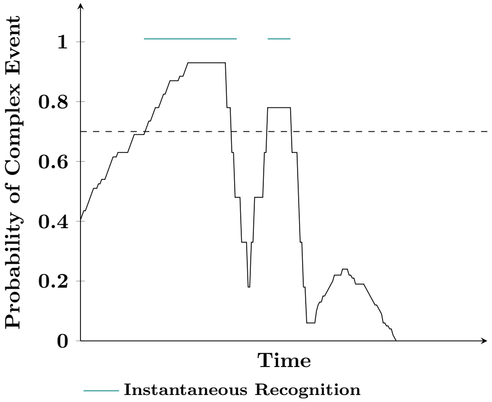
Instantaneous Recognition*



Higher accuracy than crisp reasoning in the presence of:

- several initiations and terminations;
- few probabilistic conjuncts.

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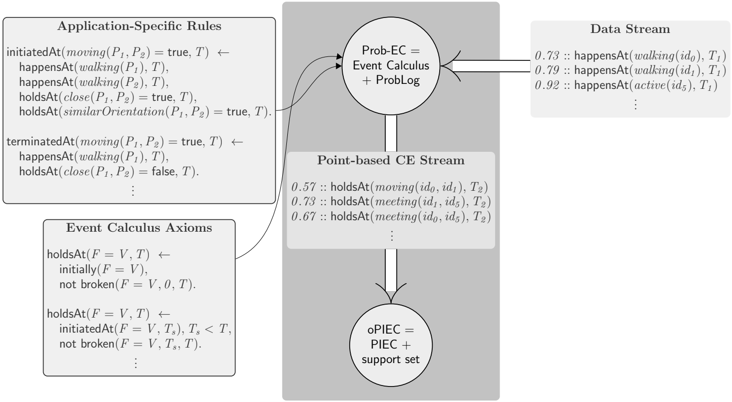
Online Probabilistic Interval-Based Event Calculus



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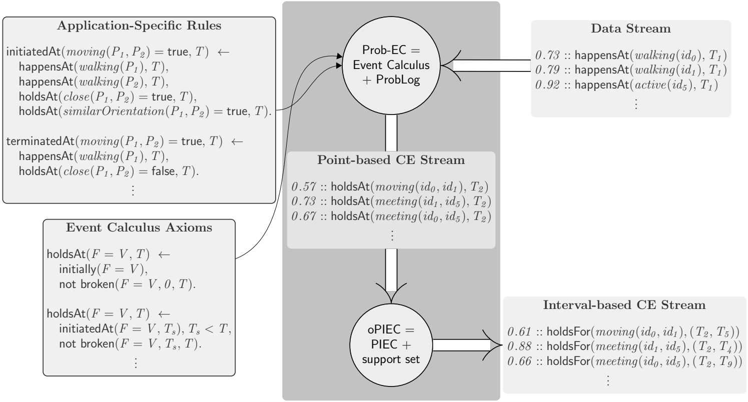
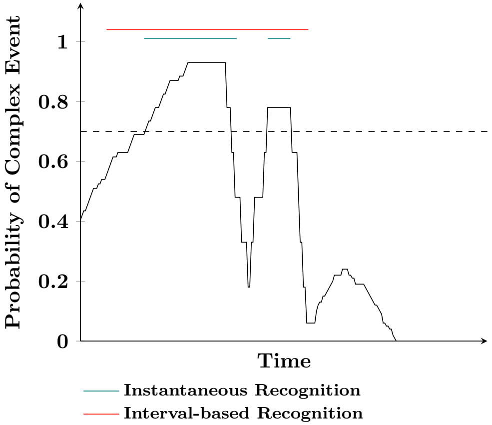


Instantaneous vs Interval-based Recognition



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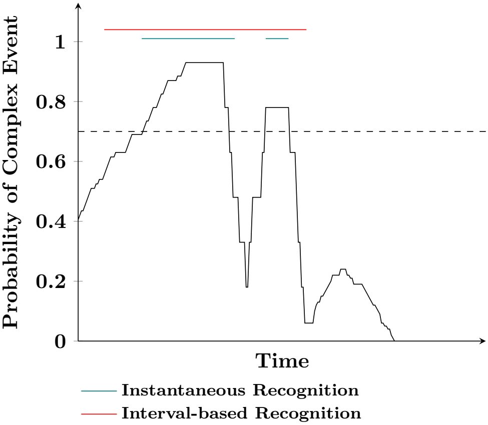
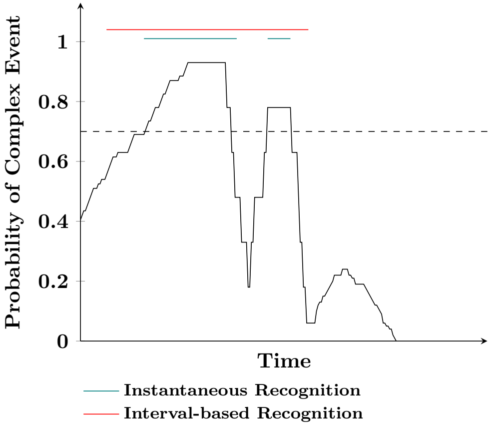


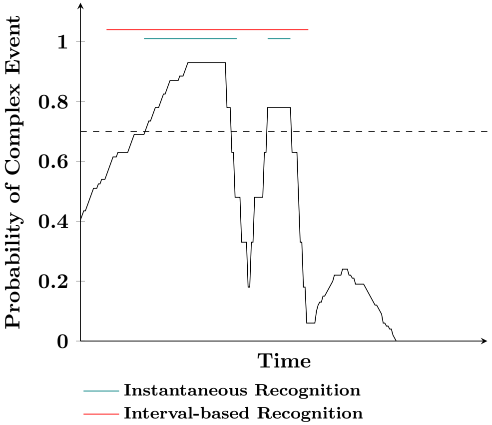
- Interval Probability: average probability of the time-points it contains.

Instantaneous vs Interval-based Recognition



- Interval Probability: average probability of the time-points it contains.
- Probabilistic Maximal Interval:
  - interval probability above a given threshold;
  - no super-interval with probability above the threshold.

Instantaneous vs Interval-based Recognition



- Interval Probability: average probability of the time-points it contains.
- Probabilistic Maximal Interval:
  - interval probability above a given threshold;
  - no super-interval with probability above the threshold.
- Probabilistic maximal interval computation via maximal non-negative sum interval computation.

Interval-based Recognition*

Interval Computation Correctness

An interval is computed iff it is a probabilistic maximal interval.

*Artikis et al, A Probabilistic Interval-based Event Calculus for Activity Recognition. Annals of Mathematics and Artificial Intelligence, 2020.

Interval-based Recognition*

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An interval is computed iff it is a probabilistic maximal interval.

Complexity

The computation of probabilistic maximal intervals is linear to the dataset size.

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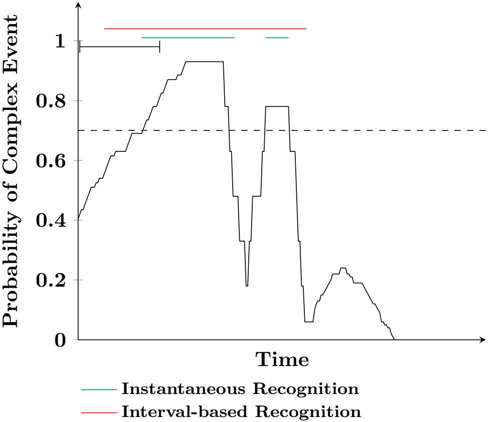
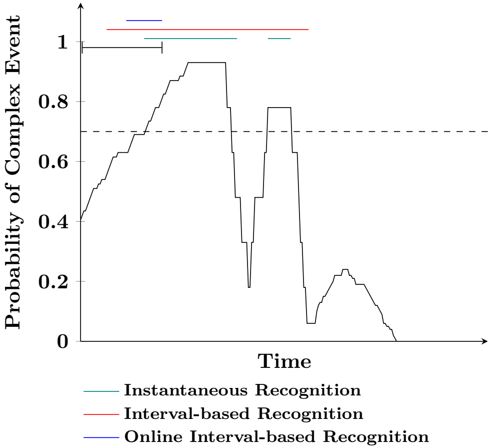
Online Interval-based Recognition



- Windowing.

Online Interval-based Recognition



- Windowing.
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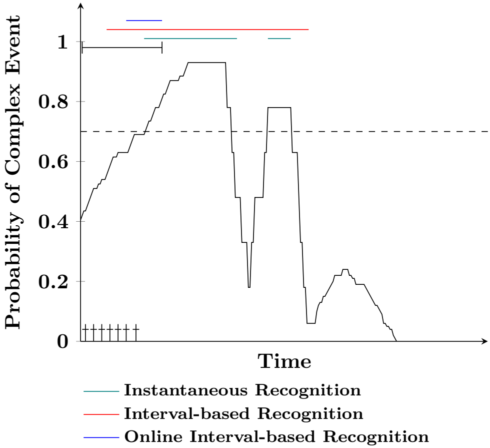
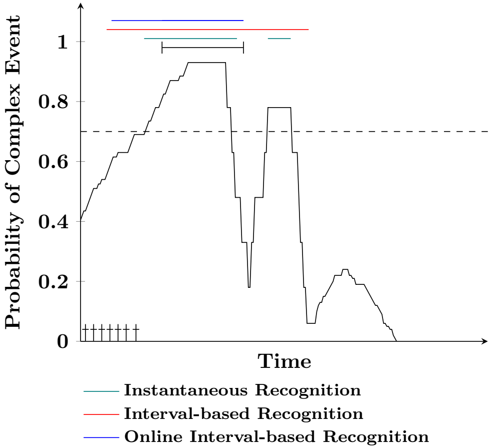


- Windowing.
- Probabilistic maximal interval computation.
- Caching potential starting points.
  - Discard time-point t iff there is a $t' < t$ that can be the starting point of a probabilistic maximal interval including t.

Online Interval-based Recognition



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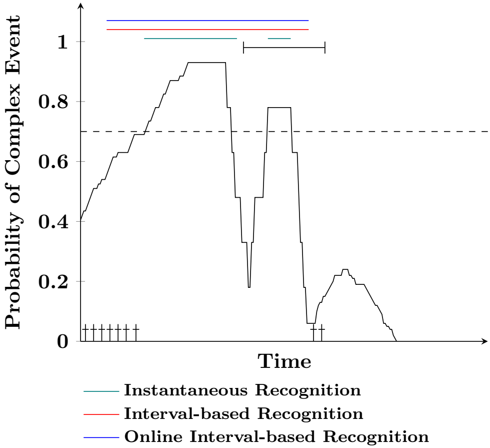

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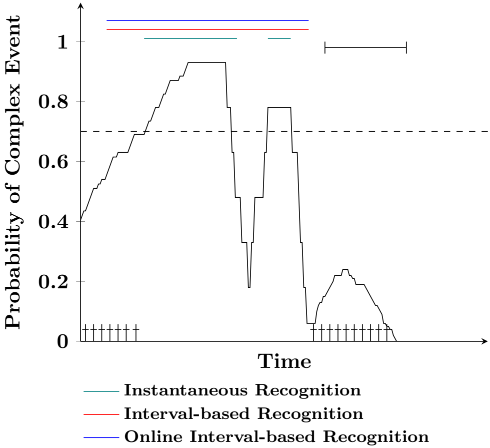

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Online Interval-based Recognition: Properties

Memory Minimality

A time-point is cached iff it may be the starting point of a future probabilistic maximal interval.

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An interval is computed iff it is a probabilistic maximal interval given the data seen so far.

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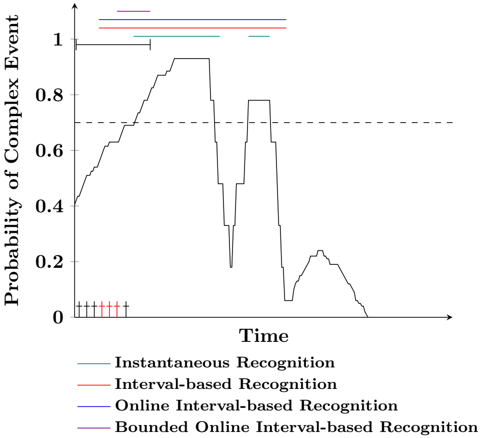
Complexity

The computation of probabistic maximal intervals is linear to the window and memory size.

Bounded Online Interval-based Recognition*



- Complex event duration statistics favor more recent potential starting points.

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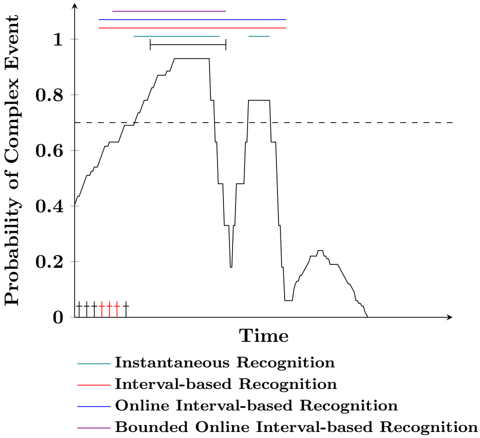
Bounded Online Interval-based Recognition*



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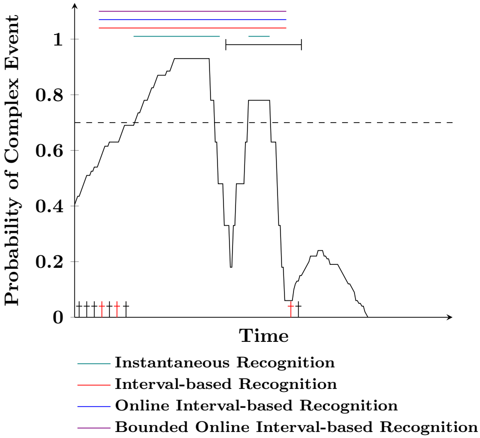

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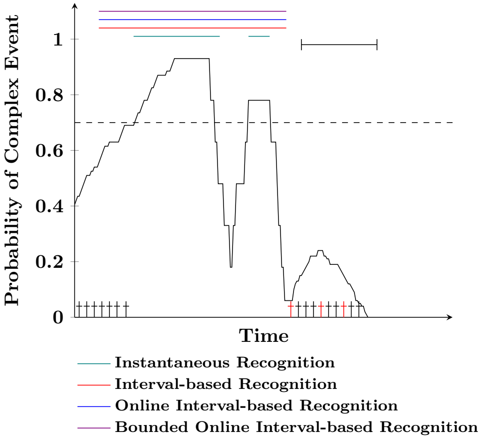

- Complex event duration statistics favor more recent potential starting points.
- Comparable accuracy to batch reasoning.

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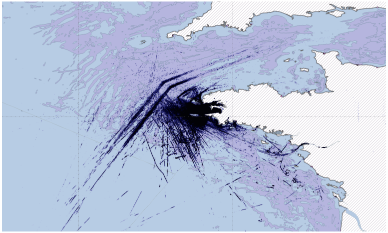
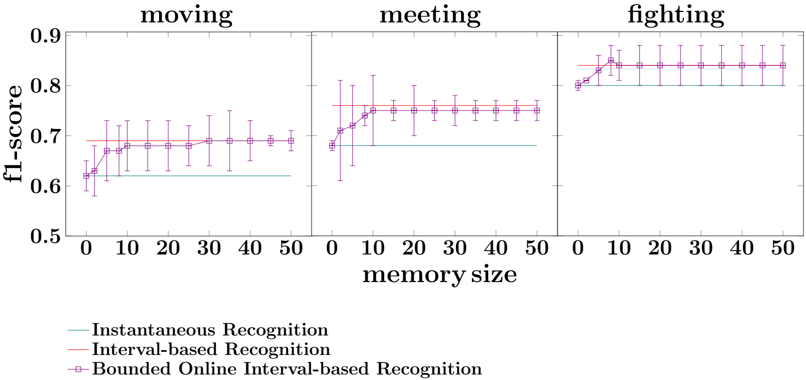
Experimental Setup



- Human Activity Recognition:
  - Input: manually annotated simple activities on individual video frames.
  - Output: maximal intervals of complex activities.
- Maritime Situational Awareness:
  - Input: vessel position signals from the area of Brest, France.
  - Output: maximal intervals of complex vessel activities.
- https://github.com/Periklismant/oPIEC

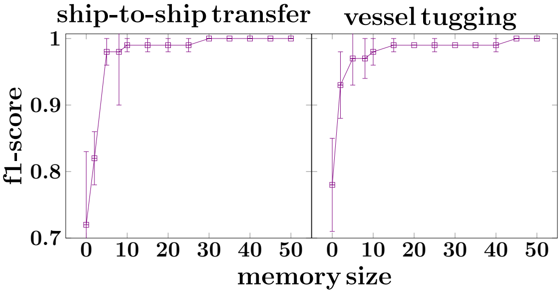
Experimental Results: Human Activity Recognition

Comparison against ground truth



Experimental Results: Maritime Situational Awareness

Performance of bounded online recognition against batch recognition



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- Online reasoning over noisy streams.
- Optimal history compression for correct interval computation.
- Reproducible evaluation on benchmark, real data.

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[†] Katzouris et al, Online Learning Probabilistic Event Calculus Theories in ASP. TPLP, 2022.

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‡Michelioudakis et al, Semi-Supervised Online Structure Learning for CER. Machine Learning, 2019.

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Topics not covered:

- Uncertainty in the event patterns[*].
- Automated construction of event patterns[†].
- Semi-supervised ML[‡].
- Complex Event Forecasting[§].

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[*] Skarlatidis et al, Probabilistic Event Calculus for Event Recognition. ACM Trans. Comput. Log., 2015.

[†] Katzouris et al, Online Learning Probabilistic Event Calculus Theories in ASP. TPLP, 2022.

[‡] Michelioudakis et al, Semi-Supervised Online Structure Learning for CER. Machine Learning, 2019.

[§] Alevizos et al, Complex Event Forecasting with Prediction Suffix Trees. VLDB Journal, 2022.

Summary & Topics not Covered

Summary:

- Online reasoning over noisy streams.
- Optimal history compression for correct interval computation.
- Reproducible evaluation on benchmark, real data.

Topics not covered:

- Uncertainty in the event patterns[*].
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Appendix

Comparison of Prob-EC implementations

	Number of Events	250	500	1000	2000
Reasoning Time	ProbLog2	19 sec	50 sec	1.75 min	**4 min**
	PITA	**3 sec**	**6 sec**	**20 sec**	Killed at 40 sec
Memory Usage	ProbLog2	**40 KB**	**50 KB**	**80 KB**	**90 KB**
	PITA	200 KB	700 KB	2 GB	Killed at 3.8 GB

Experimental Results

oPIEC$_{st}^{b}$ Execution Times in Maritime Situational Awareness