# Can Computers Understand what is Happening? A Tutorial on Complex Event Recognition (CER)

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https://cer.iit.demokritos.gr

# About the Tutorial

Contributors:

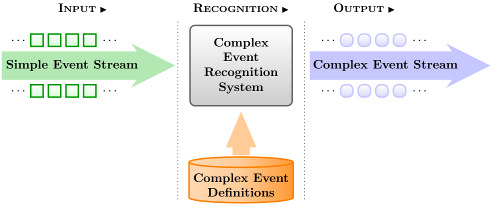
- Elias Alevizos.
- Manolis Pitsikalis.
- Efthimis Tsilionis.

Resources: http://cer.iit.demokritos.gr

- Slides: http://cer.iit.demokritos.gr/talks
- Code: http://cer.iit.demokritos.gr/software
- Data: http://cer.iit.demokritos.gr/datasets
- Opportunities for (funded) collaboration: job openings and topics for BSc/MSc theses and internships

# Complex Event Recognition & Applications

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

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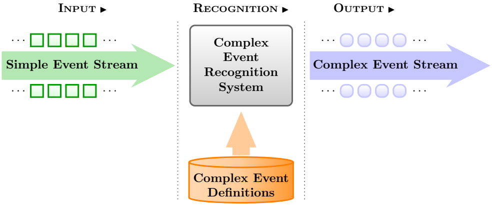


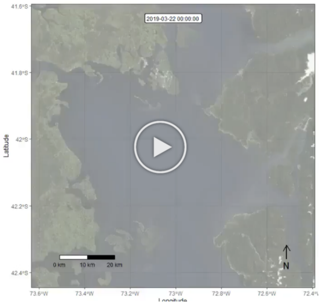


https://rdcu.be/cNkQE

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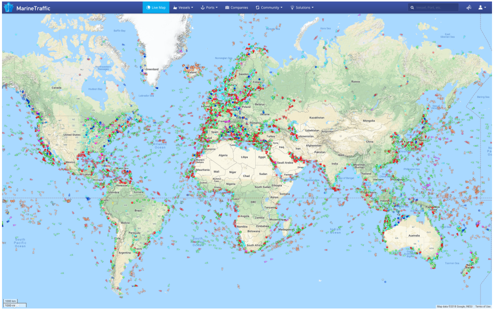


http://www.marinetraffic.com

*Artikis and Zissis, Guide to Maritime Informatics, Springer, 2021.

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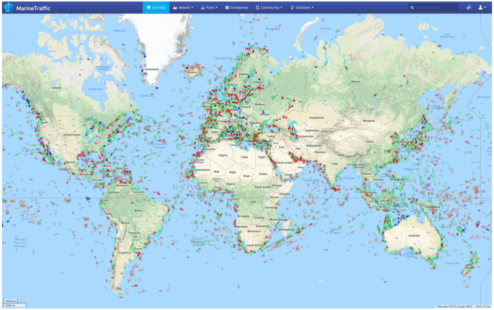


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https://cer.iit.demokritos.gr (fishing vessel)

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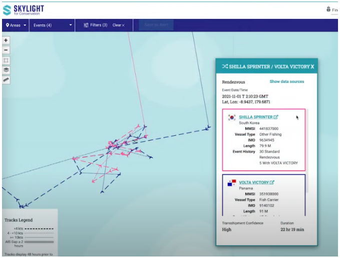
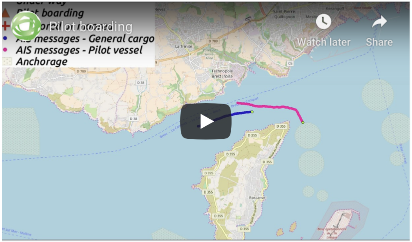
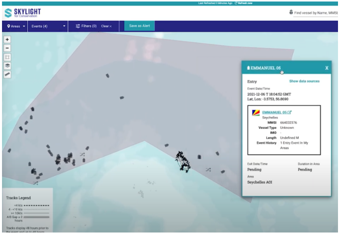
https://cer.iit.demokritos.gr (tugging)




https://www.skylight.global (rendez-vous)




https://cer.iit.demokritos.gr (pilot boarding)




https://www.skylight.global (enter area)

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# Data Challenges

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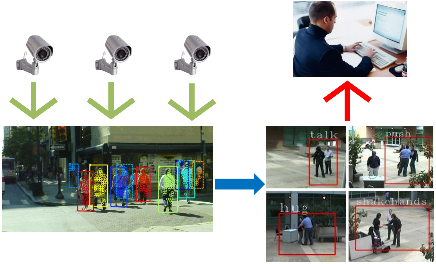
- Lack of Veracity: GPS manipulation, vessels reporting false identity, communication gaps.
- Distribution: Vessels operating across the globe.

# Human Activity Recognition



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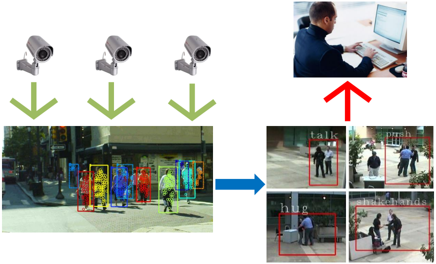



https://cer.iit.demokritos.gr (activity recognition)

# Human Activity Recognition

| Input | Output |
|---|---|
| 340 $inactive(id_0)$ | |
| 340 $p(id_0) = (20.88, -11.90)$ | |
| 340 $appear(id_0)$ | |
| 340 $walking(id_2)$ | |
| 340 $p(id_2) = (25.88, -19.80)$ | |
| 340 $active(id_1)$ | |
| 340 $p(id_1) = (20.88, -11.90)$ | |
| 340 $walking(id_3)$ | |
| 340 $p(id_3) = (24.78, -18.77)$ | |
| 380 $walking(id_3)$ | |
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| Input | Output |
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| 340 $inactive(id_0)$ | 340 $left\_object(id_1, id_0)$ |
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| 340 $inactive(id_0)$ | 340 $left\_object(id_1, id_0)$ |
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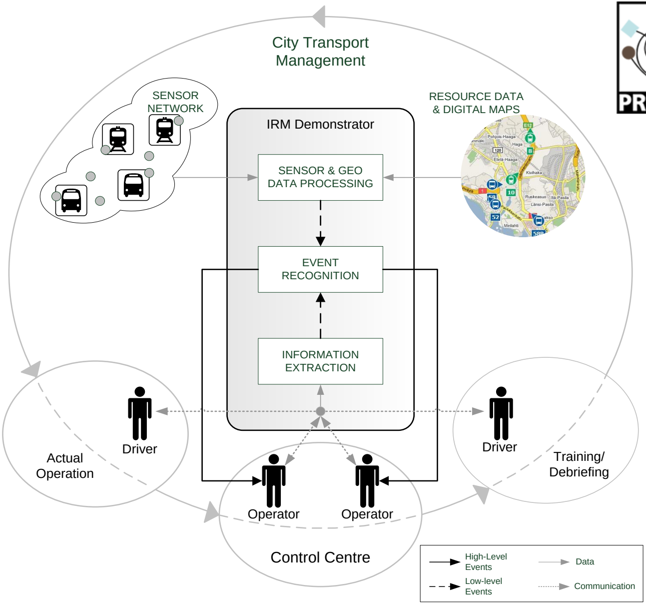
# City Transport & Traffic Management



# Credit Card Fraud Recognition


Simple events:

- Credit card transactions from all over the world.

Complex events:

- Cloned card — a credit card is being used simultaneously in different countries.
- New high use — the card is being frequently used in merchants or countries never used before.
- Potential batch fraud — many transactions from multiple cards in the same point-of-sale terminal in high amounts.

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- Fraudulent transactions: 0.1% of the total number of transactions.
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- Erroneous transactions, missing fields.

# Requirements

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- Reasoning under uncertainty
  - to deal with various types of noise.
- Complex event forecasting
  - to support proactive decision-making.

# Course Structure

- Introduction to Complex Event Recognition (CER).
  - We have Deep Learning and it seems to work — can we go home now?
- Formal Models for CER
  - ... including interval-based and incremental CER.
- Probabilistic CER.
- Complex Event Forecasting.
- Open issues & further research.

# Complex Event Recognition & Related Research

# Complex Event Recognition vs DataBase Management Systems*

Complex event recognition (CER) systems:

- Process data without storing them.

*Gugola and Margara, Processing Flows of Information: From Data Stream to Complex Event Processing. ACM Computing Surveys, 2012.

# Complex Event Recognition vs DataBase Management Systems*

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- Latency requirements are very strict.

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Data stream management systems:

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- Represent complex temporal patterns of events.
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  - A sequence of transactions using the same credit card, with an increasing amount withdrawn or spent, in a short period of time, in large distances.

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- More often than not, background knowledge is available — let's use it!

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# Models of Complex Event Recognition

# Models of Complex Event Recognition Systems

- Data model.
- Time model.
- Pattern language model.
- Processing model.
- Deployment model.

# Data Model

- An event is an object in the form of a tuple of data components, signifying an activity and holding certain relationships to other events by time, causality and aggregation.
- An event with $N$ attributes can be represented as $EventType(Attr_1, \ldots, Attr_N, T)$ where the timestamp $T$ is
  - a point for an instantaneous event;
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- For output events, $T$ is typically the result of reasoning on the timestamps of input events.
- Event streams are typically heterogeneous: events have different payload (number and type of attributes).

# Data Model: Examples

Maritime situational awareness:

- Instantaneous input/simple event:
  $speedChange(vessel_{17}, high, 10{:}15{:}02)$.
- Durative input/simple event:
  $stopped(vessel_{22}, [10{:}23{:}12, 10{:}32{:}10])$.

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- Durative CE: $illegalFishing(vessel_{45}, [9{:}26{:}12, 12{:}42{:}16])$.

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- Durative CE: $illegalFishing(vessel_{45}, [9{:}26{:}12, 12{:}42{:}16])$.
- Output events (CEs) are often relational.
- Durative, relational CE: $tugging(vessel_{72}, vessel_{33}, [10{:}23{:}12, 10{:}57{:}10])$.

# Time Model

Implicit representation (eg, in data stream management systems):

- Event timestamps are used for ordering events before entering the CER engine, and ignored afterwards.
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Explicit representation (CER):

- Event timestamps are explicitly used in pattern matching.
  - Human activity recognition: two people are said to be moving together if they are walking at the same time.
  - Credit card fraud detection: increasing amounts withdrawn within minutes.

# Pattern Language Model

- CER refers to matching patterns among the incoming streams of simple events (SE)s.
- Thus, we need a language for expressing such patterns.
- We present a basic event algebra with common operators.
- Some systems extend this algebra with additional operators.

# A Simple Unifying Event Algebra

$$
\begin{array}{rlll}
ce ::= & se & | & \\
& ce_1 \; ; \; ce_2 & | & \textit{Sequence} \\
& ce_1 \; \vee \; ce_2 & | & \textit{Disjunction} \\
& ce^* & | & \textit{Iteration} \\
& \neg \; ce & | & \textit{Negation} \\
& \sigma_\theta(ce) & | & \textit{Selection} \\
& \pi_m(ce) & | & \textit{Projection} \\
& [ce]_{T_1}^{T_2} & & \textit{Windowing} \text{ (from } T_1 \text{ to } T_2\text{)}
\end{array}
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- *Sequence*: Two events following each other in time.

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- The combination of *Sequence* and *Disjunction* expresses Conjunction (both events occurring).

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| | $\pi_m(ce)$ | \| *Projection* |
| | $[ce]_{T_1}^{T_2}$ | *Windowing* (from $T_1$ to $T_2$) |

- *Iteration*: An event occurring $N$ times in sequence, where $N \geq 0$. This operation is similar to the *Kleene star* operation in regular expressions, the difference being that *Kleene star* is unbounded.

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- *Negation*: Absence of event occurrence.
- *Selection*: Select those events whose attributes satisfy a set of predicates/relations $\theta$, temporal or otherwise.

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$$

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- *Windowing*: Evaluate the conditions of an event pattern within a specified time window.

# Types of Window

- Logical (time-based) windows: bounds are defined as a function of time.
  - Example: Match a pattern only on the events received in the last 10 minutes.
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  - Example: Match a pattern only on the last 10 received events.
- In either case, both bounds advance with a pre-defined logical or physical step.
  - Pane windows: overlapping sliding windows.
  - Tumble windows: non-overlapping sliding windows.

# Processing Model

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- The single selection strategy produces either $(\alpha, 1),\ (\beta, 3)$ or $(\alpha, 2),\ (\beta, 3)$.
- The single selection strategy represents a family of strategies, depending on the matches actually chosen among all possible ones.

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  - ... assuming a multiple selection strategy.
- The selected consumption policy produces $(\alpha, 1),\ (\beta, 2)$.
  - $(\alpha, 1)$ is consumed when the pattern is matched (at the arrival of $(\beta, 2)$), and thus no longer available when $(\beta, 3)$ arrives.
  - Once $(\alpha, 1)$ is consumed, it is not considered in ANY other pattern!

# Deployment Model

- Centralised CER: all incoming event streams are processed by a single node.
- Distributed CER: several nodes are utilised.
- Distribution type:
  - Events. CER on different (possibly disjoint) streams.
  - Patterns. CER on different patterns (possibly compiled by a pattern rewriting process).

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  - Patterns. CER on different patterns (possibly compiled by a pattern rewriting process).
- Distribution method:
  - Cluster. CER by means of strongly connected machines.
  - Wide area network. Mimimise network usage and support data privacy by processing events as close as possible to the sources.
  - In-situ processing. Processing events at the sources.

# A Typical Complex Event Recognition Language (SASE)

# Event Algebra

Core components of an event algebra with point-based semantics:

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- Negation (˜ or !) verifies the absence of certain events in a sequence — eg SEQ($A, !B, C$).
- Value predicates specify constraints on the event attributes
  - Aggregate functions *max*, *min*, *count*, *sum*, *avg*.

# Event Algebra

- Composition refers to:
  - Union of constraints — eg $\text{SEQ}(A, B, C) \cup \text{SEQ}(A, D, E)$.
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- Windowing (WITHIN) restricts a CE definition to a specific time period.

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- Skip-till-any-match: Most flexible (and expensive). Detects every possible occurrence. For the previous example, $a_1, b_2, c_1$ will also be detected.

# Example (1)

PATTERN SEQ(*gapStart a*, *gapEnd b*, *speedChange c*)
WHERE partition-contiguity
AND *vesselId*
AND *c.velocity* $>$ *30*
WITHIN 3600

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Quickly moving away from an area of suspicious activity:

- After a communication gap, ...
- a vessel changes speed to over 30 knots.
- Partition contiguity ensures that $a, b, c$ refer to the same vessel (*vesselId*) and are contiguous with respect to that vessel.

# Example (2)

PATTERN SEQ$($*lowSpeedStart a*$,$ *turn*$+$ *b*$,$ *lowSpeedEnd c*$)$
WHERE skip-till-next-match
AND *vesselId*
AND $b[i].heading - b[i-1].heading > 90$
WITHIN 21600

# Example (2)

PATTERN SEQ($lowSpeedStart\ a,\ turn+\ b,\ lowSpeedEnd\ c$)
WHERE skip-till-next-match
AND *vesselId*
AND $b[i].heading - b[i-1].heading > 90$
WITHIN 21600

Fishing pattern:

- A vessel slows down, ...
- begins a series of turns, where, for each pair of successive turns, their difference in heading is more than 90 degrees, ...
- and subsequently the vessel stops moving at a low speed.

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Next: An expressive language with an efficient implementation.